A Multifactor Approach in Understanding Asset Pricing Anomalies

An empirical study of the factor model in the Budapest Stock Market

Naffa Helena

Spring 2009

Budapest

Table of Contents

Table of Figures

Tables

“What is a cynic? A man who knows the price of everything, and the value of nothing.”

Oscar Wilde – Lady Windermere’s Fan

1 Introduction

An anomaly is usually a disorder, a deviation from the norm. In natural science, it has induced researchers to formulate new theories. In finance however, what could not be explained by traditional asset pricing theories[1] was hastily arbitrated, and later labelled an anomaly. The multifactor model devised by Fama and French on the other hand, is quite successful in explaining these anomalies, and therefore, the new theory is able to incorporate them in their asset pricing formula.

In my thesis, I introduce the topic of observed abnormal[2] market returns as being justifiable premiums versus signifying market inefficiencies. The phenomenon of anomalies is best explained by an amalgam of available financial literature. In such an explanation, the Efficient Market Hypothesis plays a central role in defining a standard for asset pricing in an ideal world. I will introduce the capital asset pricing model approach. In contrast with this, I discuss an extended model devised by Fama of asset pricing that incorporates factors relating to the anomalies discussed. This will familiarise the reader with the methodologies applied by different theorists to test the new model against traditional approaches. The critics of the new Fama model rebuke with an apparent rationale: the new model is specific to the set of data examined by Fama; therefore its high precision in forecasting asset returns is not a coincidence. I shall attempt to reveal the relevance of the model to the Hungarian market. My approach will apply the formula to the emerging Budapest Stock Exchange shares using an un-ambitious time series from September 2003 till September, 2008.

[1] Traditional asset pricing theories cover the CAPM and the factor model (APT)
[2] Abnormal returns denotes returns exceeding market yield, i.e. (r_i-r_m)

"I'd be a bum in the street with a tin cup if the markets were efficient."

Warren Buffett

2 The Efficient Market Hypothesis

Despite the above quote from Warren Buffett, I with to study informational efficiency in stock markets. When markets are efficient, they work smoothly whereby the possession of new information causes no added-value. From this stems the assumption in financial models that additional information should come at no cost, as it is already reflected in prices. It is much ore likely to have transparent pricing for financial instruments traded on stock markets e.g. stocks, bonds, commodities. But the matter of fact is that the efficient market hypothesis fails in practice. Investments traded on the stock market by far do not represent to complete investment portfolio available to investors. Other financial products are available on different platforms, most of which are less transparent than stock markets. The efficient market hypothesis (EMH), however, makes assumptions that limit its validity to a theoretical market. Amongst these assumptions is that all transactions are transparent, which makes pricing fair (unbiased), as they incorporate all available information including the expectations of the market participants of the future shaping of the market. Information, as defined by the theory, is anything that affects prices in a way unknown in the present appearing randomly in the future. For this reason, it is not possible to consistently outperform the market by taking advantage of news the market already knows, except when an investor is lucky.

The efficient market hypothesis was first coined by Louis Bachelier, a French mathematician. In his 1900 dissertation “Théorie de la Spéculation” he “begins the mathematical modelling of stock price movements and formulates the principle that ‘the expectation of the speculator is zero.’ Obviously, he understands here by expectation the conditional expectation given the past information. In other words, he implicitly accepts as an axiom that the market evaluates assets using a martingale measure.” (Courtault et al.

2000 p. 343) Yet his work was overlooked for decades until the mid 1960s when Paul Samuelson stumbled upon the dissertation and soon it became a hot topic for financial economists. However, the efficient market theory owes its refined details to Professor Eugene Fama of the University of Chicago Graduate School of Business. Fama started the formation of the theory as a PhD. dissertation and ended up as a life-long research. In 1970 he published a review of both the theory and the evidence for the hypothesis. The paper extended and fine-tuned the theory; in addition, it included the definitions for three forms of market efficiency: the weak, the semi-strong and the strong form of market efficiency.

2.1 Theory

The theory assumes that market participants apart from being utility maximising, also have rational expectations. This includes the assumption that even though individuals may be wrong, the population as a whole is correct; and that people adjust their expectations according to new information. When faced with new information, some investors will overreact and others will under react. In summery, reactions will be random, but will have a constant volatility, and a known distribution function. Thus, the net effect does not allow for abnormal profit to be realised especially when considering transaction costs and spreads.

Fama says that an efficient market is one that quickly adjusts to new information. It prevails in markets where prices "fully reflect" available data. This constitutes the impossibility of attainting extra profits by trading on the basis of knowledge of information already incorporated.

It means that in its strongest form, there should be no cost of information. We know that this in untrue, and that a whole industry is based on selling information. This is why the need arises to further define efficiency of the markets. This has taken the form 3 levels of information integration; the weak form of efficiency, the semi-strong form of efficiency and the strong form of efficiency are discussed below.

2.1.1 Weak Form of Efficiency

In its weakest form, the efficient market hypothesis assumes that all historical share prices are already incorporated into the pricing of assets. Therefore, no excess profits can be earned by basing investment strategies on past returns. This implies that technical analysis, which studies formations in past returns, is useless in predicting the future. Since past performance is already known to the market, the current situation remains unknown. This is where fundamental analysis gains attention and may be rewarding for those keen investors who do their homework on companies' financial statements.

Tests for the weak form of efficiency engage in historical data analysis using statistical and econometrical methods. Analyses concerning market value, P/E, DIV/P, and book-equity-to-market-equity influences on past data, as well as technical analysis are prevalent in such testing.

2.1.2 Semi-Strong Form of Efficiency

The levels of efficiency gradually increase their restrictions, so it is natural for the next level to include the previously stated assumptions. In addition to historical data, the semi-strong form of efficiency incorporates publicly available new information rapidly into pricing; this insinuates that fundamental analysis will yield nothing.

Testing for semi-strong form of efficiency is similar to event studies. Emergence of new information usually takes the form of quarterly or annual reports or events such as mergers, acquisitions, purchase of treasury shares, new issuances or splits. The emergence of such news should induce markets to adapt quickly. We can measure the quickness and flow of the adaptation to new information.

2.1.3 Strong Form of Efficiency

This level of efficiency constitutes the incorporation of all existing information, both public and private, into prices. In such a model no one can earn extra profits. Of course in reality laws prohibit trading using insider information. The Hungarian Capital Market Law

(Tpt CXX/2001 § 199-205) prohibits trade using information not known to the public. In the United States the Insider Trading Sanctions Act of 1984 and the Insider Trading and Securities Fraud Enforcement Act of 1988 regulates penalties for illegal insider trading "to be as high as three times the profit gained or the loss avoided from the illegal trading." [3] Relevant laws in the United Kingdom also reveal a similar standpoint. The Financial Services Act 1986 and the Financial Services and Markets Act 2000 define an offence of Market Abuse.

Testing the strong form is a test for the existence of insider trading. We attempt to reveal the investment activity of interest groups with monopoly over key decisions in the companies. This can be observed in price adjustments taking place before important announcements are made public.

[3] http://www.sec.gov/news/testimony/2006/ts092606lct.htm downloaded on 15th August, 2008

"Markets can remain irrational longer than you can remain solvent."

John Maynard Keynes

2.2 The Hypothesis Defied

Researchers argue about the validity of the efficient market hypothesis in the real markets, especially its strong form. The main set-back to the theory includes slow transmission of information, and relative power of a few market players. The market's mechanism in adapting to change in interest rates for instance, takes from a few hours to several weeks. This is the main defect, whereas according to the EMH this process ought to be instantaneous. Only a few privileged people may have prior knowledge of new laws or decisions that will affect prices. As long as actors on 'inside information' arbitrate market mispricing in a discreet manner, they can avoid being detected. As soon as such trading takes place on a wide scale, we cannot dismiss it from our study as random variables.

Another malefficiency of the real markets compared to the ideal suggested by EMH is that at extreme situations what fundamentalists consider irrational investor behaviour is actually the norm. As an instance, the last stage of a bull market is usually driven by buyers (speculators) who take little consideration of the underlying value of the asset. Contrarily, the end of a bear market witnesses a free fall as everybody attempts to close their positions regardless of the quality of the investments they hold. This observation is bolstered by the differences in stock valuation in bull markets compared to bear markets. Thus, it would make sense for rational investors to take advantage of the feigned high or low prices caused by irrational participants, by taking on opposite positions. Obviously in practice this is insufficient to prevent arising bubbles or crashes. Rational investors are aware of the irrational behaviour of the market, and at extreme times, they will need reasons superseding fundamental explanations to convince them that the market will return towards fair value. It was shown statistically, that extreme values do occur more often than a normal distribution would anticipate. And these extreme values are not confined to three sigmas[4]; a phenomenon financial literature refers to as a distribution's fat tail.

Opponents of the theory argue that there exists a small number of investors who managed to sustain their outperformance of the market for long periods of time, in a way that overrules the role of luck. These include names such as Peter Lynch and Warren Buffett. Their strategies were always to identify markets where prices did not fully reflect available information. On the other hand, proponents of the theory argue that EMH does not rule out the success of a limited number of funds through chance. Furthermore, these explanations go on to explain the success of 'star' fund managers as being the result of management skills rather than stock market prediction.

Malkiel is a famous supporter of the general validity of the efficient market hypothesis. Even he, based on empirical findings, believes that some emerging markets for example the Chinese markets, are not efficient. Malkiel warns that "the Shanghai and Shenzen markets exhibit substantial serial correlation in price trends and evidence of manipulation, contrarily to the random walk theory that is expected from markets in the United States." (Malkiel 2003 p. 23)

Moreover, the efficient market hypothesis appears to be inconsistent with some events in stock market history even in the United States. The market crash of 1987 was caused by no major news; and despite that the Monday of the crash saw the S&P 500 index fall more than 20% only in the month of October. The decline seemed to originate from nowhere, only the irrational behaviour that caused the haphazard sweep through stock markets, Malkiel continues.

Investment culture in the public's imagination also refuses the efficient market hypothesis. This may be attributed to a general misconception concerning its meaning. Many believe that EMH states that a security's price is a correct reflection of the value of the underlying company as calculated by discounting the future returns. If this were true, it would mean that a stock's price accurately envisages future results. Since this is evidently not the case,

[4] Sigma is standard deviation. About 99.7% of a normal distribution N~(0,1) is confined to three sigmas.

many people reject the hypothesis. Nevertheless, EMH does not attempt to predict future returns. Rather, the EMH states that a security's price incorporates possible projections of future happenings, based on the best information available at the time. The EMH merely estimates the performance of a stock. If the course of events veers the true value of the stock too far away from the EMH prediction, even then the deviation does not challenge the validity of EMH.

2.3 Capital Asset Pricing Model

So far, we discussed price changes in singular share portfolios. On the other hand, when an investment portfolio includes more than one type of instrument, then the relative pricing to each other steps in as a determining factor. Financial theory accepts the notion that a share's return should be proportional to the risk incurred by its holder. Because differences in expected returns of different investment opportunities reflect different levels of risk, we are in need of an equilibrium model. At the birth of the efficient market hypothesis, the risk-return equilibrium model was the CAPM, a development of Sharpe and Lintner.

The Capital Asset Pricing Model assumes investors to be utility maximising agents. It also assumes that all investors behave in the same manner. Thus, by aggregating utilities, a securities market line (SML) can be defined and an optimal investment portfolio can be determined. The CAPM incorporates two types of returns, the risk free returns of the government bonds and beta times the return on the market portfolio. The following equation is the basis of this model:

$$E(r_i) = r_f + \beta[E(r_m) - r_f]$$

where $E(r_i)$ is the expected return of the asset in question; r_f is the risk free return rate; r_m being the market risk; and β the sensitivity of the particular share to movements in the market return. Formally, β's definition is:

$$\beta_i = \frac{Cov(r_i, r_m)}{\sigma_m^2}$$

where r_i is the return of the asset, r_m is the return of the market portfolio, and σ_m^2 is the variance of the market portfolio.

This form of the CAPM is a specific case of the more generalised form:

$$E(r_i) = \alpha_i + \beta[E(r_m) - r_f] + \varepsilon_i$$

The above linear regression provides a method for estimating α_i the mispricing of the stock relative to the market; and β the stock sensitivity to the market risk factor; and ε_i the residual return.

Active portfolio managers seek to gain incremental returns with a positive alpha, but if markets are efficient and the Sharpe-Litner version of the CAPM is the correct model, then alpha ought to be zero. Statistical inference to test the hypothesis $\alpha=0$ is the basis of many empirical tests of the validity of different versions of the CAPM.

Sharpe received the Nobel memorial prize in 1990 for his work on the CAPM, this is when his Sharpe ratio gained popularity. The ratio describes how much excess return the investor is receiving for the extra volatility that he is enduring for holding a riskier asset.

$$S(x) = \frac{(r_x - r_f)}{\sigma_x}$$

where x is the investment, r_x is the average rate of return of x, r_f is the risk-free return and σ_x is the standard deviation of r(x).

The weakness of the ratio is that it assumes that all asset returns are normally distributed. Abnormalities like kurtosis, fatter tails and higher peaks, or skewness on the distribution can be a problematic for the ratio, as standard deviation doesn't have the same effectiveness when these problems exist.

“An economist was strolling down the street with a companion when they come upon a $100 bill lying on the ground. As the companion reached down to pick it up, the economist said ‘don’t bother - if it was a real $100 bill, someone would have already picked it up’.”

Andrew Lo (2000)

2.4 An Alternative Theory: Arbitrage Pricing Theory

A substitute and concurrent theory to the CAPM is one that incorporates multiple factors in explaining the movement of asset prices. The arbitrage pricing model (APT) on the other hand approaches pricing from a different aspect. It is rarely successful to analyse portfolio risks by assessing the weighted sum of its components. Equity portfolios are far more diverse and enormously large for separate component assessment, and the correlation existing between the elements would make a calculation as such untrue. Rather, the portfolio’s risk should be viewed as a single product’s innate risk. The APT represents portfolio risk by a factor model that is linear, where returns are a sum of risk factor returns. Factors may range from macroeconomic to fundamental market indices weighted by sensitivities to changes in each factor. These sensitivities are called factor-specific beta coefficients or more commonly, factor loadings. In addition, the firm-specific or idiosyncratic return is added as a noise factor. This last part, as is the case with all econometric models, is indispensable in explaining whatever the original factors failed to include. In contrast with the CAPM, this is not an equilibrium model; it is not concerned with the efficient portfolio of the investor. Rather, the APT model calculates asset pricing using the different factors and assumes that in the case market pricing deviates from the price suggested by the model, arbitrageurs will make use of the imbalance and veer pricing back to equilibrium levels. At its simplest form, the arbitrage pricing model can have one factor only, the market portfolio factor. This form will give similar results to the CAPM.

Stephen Ross, who initiated APT in 1976, explained that an asset’s price today should equal the sum of discounted future cash flows, where the expected return of the asset is a linear function of the various factors. According to this definition, risky asset return will satisfy the following equation:

$$E(r_i) = r_f + \beta_{i1}RP_1 + \beta_{i2}RP_2 + ... + \beta_{in}RP_n$$

$$r_i = E(r_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + ... + \beta_{in}F_n + \varepsilon_i$$

Where $E(r_i)$ is the expected return of the asset, RP_n is risk premium of the factor, r_f the risk-free rate, F_n the factors, β_{in} is the sensitivity of the asset to factor *n*, also known as factor loading, and ε_i is the asset's idiosyncratic risk.

Factors may be economic factors (such as interest rates, inflation, GDP) financial factors (market indices, yield curves, exchange rates) fundamentals (like price/earnings ratios, dividend yields), or statistical (e.g. principal component analysis, factor analysis.) The factor model's beta coefficients i.e. sensitivities may be estimated using cross-sectional regression or time series techniques.

Well-diversified portfolios are assumed in the model. This incorporates that ε the disturbance factor be composed of sufficiently uncorrelated terms so that the disturbance term for a substantially large portfolio vanishes. The market portfolio will be well-diversified if no single asset accounts for a significant proportion of aggregate wealth. A further assumption is that there is perfect competition in the market, and that factors do not outnumber the assets in the portfolio in order to avoid the problem of matrix singularity.

What is the consequence in the case returns deviate from what the model projects? The name of the model suggests arbitrage. Arbitrage is taking advantage of a state of imbalance in a market thus attaining risk free profit. Two known approaches of arbitrage are cited in Makara (2006) p 2:

There is no static arbitrage if there is no such $x \in \Re^N$ where,

$$Vx > 0 \text{ and } p'x \leq 0 \qquad (1)$$

Or $\quad Vx \geq 0$ and $p'x < 0$ (2)

If there exists $x \in \Re^N$ for which equation 1 is true then there is type 1 of arbitrage. It means that an arbitrageur has the chance of gaining money in the future, but it costs him nothing at present. In case there is such an $x \in \Re^N$ which satisfies equation 2, then arbitrage of type 2 steps in. In plain words, it means that the arbitrageur will receive money at present with no prospects of losing in the future.

The mechanism of arbitrage constitutes that investors trade at least two assets; one of them is mispriced according to the model. The relatively expensive asset is sold to finance the purchase of the relatively cheap asset. The correctly priced asset may be a synthetic product, which is a portfolio of other correctly priced assets combined to reproduce the risk and the return of the original asset. The synthetic product should have the same exposure to each of the factor of the APT model as the asset it wishes to reproduce.

2.5 Relationship between the CAPM and APT

The two models approach asset pricing from different aspects. The APT is less restrictive in its assumptions than the CAPM. It is a rather explanatory model as opposed to statistical. It assumes investors will each hold a portfolio unique to their risk receptiveness with a unique beta, as opposed to the identical market portfolio presumed by the CAPM.

Moreover, the APT presumes an infinite number of investments, which in turn lead to the disappearance of firm-specific risk. It can be viewed as a supply-side model, as its beta coefficients reflect sensitivity of the underlying asset to the different factors. In this sense, factor changes will cause sizable shifts in the asset's expected returns. On the other hand, the CAPM is a demand-side model. Its results arise from the investors' utility function maximisation problem, and from the resultant market equilibrium. As investors can be considered to be consumers of the asset, the demand approach is reasonable.

2.6 When Theories Fail, Anomalies Prevail

Since researchers recognised the existence of asset mispricing that surpassed available economic theories' ability to explain them, the study of anomalies began. It is always easier to determine the causes of the occurrences with the benefit of hindsight. But when they are actually taking place, it is not easy to identify them, let alone incorporate them into pricing models. This is the benefit market speculators get for their efforts in identifying anomalies. When an anomaly gets detected, and enough arbitrageurs have made money, as the self-fulfilling prophecy foretells us, the trend disappears. This is when the anomaly is ripe for public introduction and the race begins for providing extensive analysis in financial journals. Amongst the reasons for anomalies are: tax evasion, window-dressing of portfolio fund managers, or expected premium for trading opposite positions to insiders. Here, I introduce the most famous anomalies that prevailed in the past decades.

2.6.1 The Calendar Effect

The calendar effect incorporates several observances related to the calendar schedule. Rises and falls that were observed on specific days of the week or on months of the year. Often calendar-related anomalies are related to prescheduled deadlines of corporate liabilities or simply to sociological habits of investors.

The most common is the *January effect* or in other words end-of-year effect. It was noticed from the mid 1960s that at the end of each year, prices of stocks fell noticeably, with no reasoning found in the fundamentals of the companies. It was found that before the end of the fiscal year on 31st December, for tax optimising purposes, investors closed their positions to realise their losses. Gaining positions were closed for reasons of boosting fund managers' report figures, and thus their end-year bonuses. The resultant selling pressure caused prices of assets to fall. The first days of the New Year, hence, were suitable for these investors to buy back, or for others who saw an opportunity in the low December prices to buy. This tendency caused a jump in prices in the first five days of January each year, and, therefore became known as the January effect. It is interesting to notice that this effect mainly affected small cap stock. Robert Haugen measured monthly returns in stocks from 1927 – 2001, his findings are visible in the bar chart below. (Source:

Haugen's chart taken from http://en.wikipedia.org/wiki/January_effect downloaded 5th September, 2008)

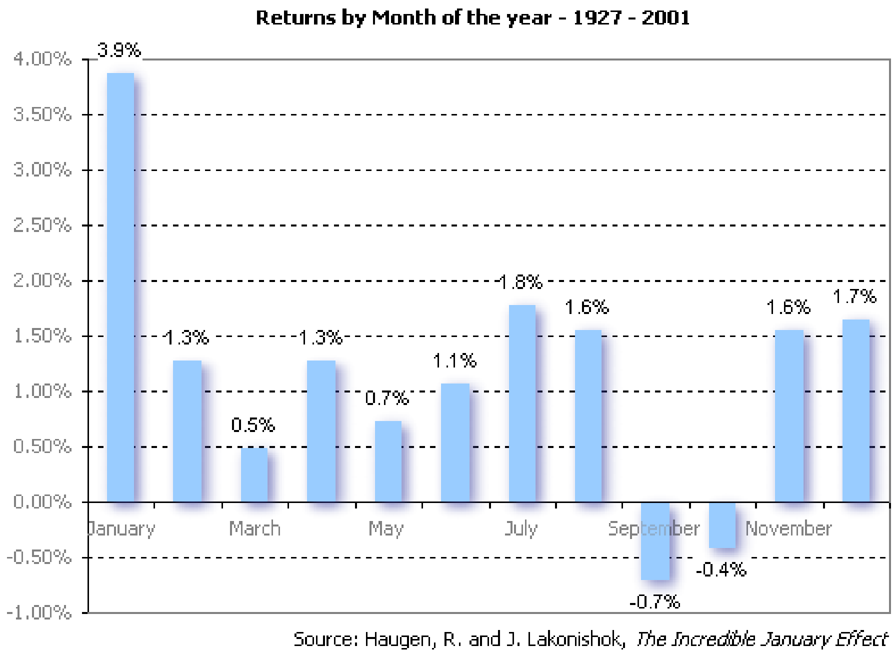


Figure 1: Haugen's monthly returns for years 1927-2001

After the January effect became widely known to the public, it slowly shifted to December, causing the so-called Santa Claus rally. But soon, the anomaly disappeared. The *Monday effect* was slightly less obvious. It was observed that stocks traded on Monday will follow the prevailing trend from the previous Friday. For example, if the market was in an upward trend on Friday, it should continue on Monday where it left off and resume its rise. Moreover, Monday returns did not reflect the weekend days' return of capital; markets seemed not to count the weekend in calculating returns. Hence the notion, that when turning daily return to yearly and vice versa, the multiplier in this case is 250 working days as opposed to 365 days of the year.

Julia Tímári (2005) studied the calendar effect on the Budapest Stock Exchange for the period January, 1991 to December 2004. The methodology included the use of dummy variables to represent days of the week as the following equation suggests: (Tímári 2005 p. 23)

$r_t = c_1 D_{1t} + c_2 D_{2t} + c_3 D_{3t} + c_4 D_{4t} + c_5 D_{5t} + \varepsilon_t$, where:

r_t is the logarithmic return of the asset on day t

$D_{1t}, D_{2t}, \ldots$: are dummy variables, i.e. D_{1t} takes on 1 if t is a Monday, otherwise it takes on the value of zero.

The testing period was divided into two intervals for the following reasons. The first period from January, 1991 – December 1997 witnessed the re-opening of the Budapest Stock Exchange. The initial phase was stable yet immature. The regression showed two days with significant determining power over the shaping of returns. Wednesday and Friday were the ones with determining power, and Monday was merely on the verge of reaching the 10% significance level. Surprisingly, all days yielded positive returns as shown in table 1. The star indicates significant results at a 10% significance level; the double stars indicate significance at 5%. (Source: Tímári 2005 p. 24-25)

	Coefficient	Std. Error	t-Statistic	Prob.	
C(1)	0.001267	0.000793	1.597543	0.1103	
C(2)	0.000779	0.000776	1.004324	0.3154	
C(3)	0.001953	0.000783	2.495204	0.0127	**
C(4)	0.000517	0.000777	0.665301	0.5059	
C(5)	0.001390	0.000783	1.776169	0.0759	*

R-squared	0.001110	Mean dependent var	0.001183
Adjusted R-squared	-0.001170	S.D. dependent var	0.014656
S.E. of regression	0.014664	Akaike info criterion	-5.603956
Sum squared resid	0.376970	Schwarz criterion	-5.588393
Log likelihood	4930.877	Durbin-Watson stat	1.665682
F-statistic	0.486879		

Table 1: The first period's regression January 1991- December 1997

The years following the regime-change saw high inflation, which induces the reconsideration of nominal returns.

In the latter phase that covers January 1998 to December 2004, daily average returns do not significantly deviate from zero, which means that the market is efficient. Moreover, we observe negative returns on some of the days. (Source: Tímári 2005 p. 25)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.001552	0.000985	1.575246	0.1154
C(2)	6.05E-05	0.000956	0.063334	0.9495
C(3)	-0.000464	0.000957	-0.485226	0.6276
C(4)	-4.31E-05	0.000958	-0.044973	0.9641
C(5)	0.000721	0.000968	0.744330	0.4568

R-squared	0.001501	Mean dependent var	0.000350
Adjusted R-squared	-0.000792	S.D. dependent var	0.018027
S.E. of regression	0.018034	Akaike info criterion	-5.190278
Sum squared resid	0.566531	Schwarz criterion	-5.174635
Log likelihood	4538.708	Durbin-Watson stat	1.906013
F-statistic	0.654737		

Table 2: The second period's regression January 1998 – December 2004

Between 1997 and 1999 volatility of the returns was considerable, in both positive as well as negative directions. This was primarily the consequence of the Russian crisis that especially affected the Hungarian pharmaceutical companies. Later, contagion reached the Asian Tigers. From the test results, we can deduce that the Monday-Friday effect is not present in the Hungarian market. Observations reveal abnormal patterns before the turn of the millennium (around 1998), but this is due to instability of foreign markets. Therefore, the Hungarian market can be considered efficient in this sense.

This test was repeated with the exclusion of outliers. Results bolstered the previously introduced conclusions. Where significant days were observed in the previous testing stage, now, with the exclusion of the extreme values, those days became even more significant. This was caused by the lower standard error. Some days that were insignificant, passed the significance threshold at 5% or 10%. Further evidence that corroborates previously attained results is that the signs of the coefficients remained unchanged in general. In the few cases where change took place, values were close to zero. From this, we can deduce that anomalies were not caused by outliers. With the passing of time the anomalies lessened; in the last three years of the study period, they were undetectable. The last three years had less outlier values than in the previous periods.

This observation again corroborates the statement that the market became more efficient by this period.

Tables 1 and 2 also show the F-statistics of days of the weeks effect (DOW). The statistic measures the strength of the regression in explaining stock returns. The statistic was not significant in any of the tests, which means that stock returns are formed regardless of which day of the week it is. Tímári covered months of the year in her tests. Results were analogous to the DOW effect: it is non-existent in the Budapest Stock Exchange.

2.6.2 Earnings on Book Equity

Fama et al (1995) studied the effects of size and book-to-market value on earnings. Their findings proved that earnings are a function of market, size and book equity-to-market equity (BE/ME) factors. High BE/ME ratios signalled poor earnings and low BE/ME ratios indicated high returns on capital. This can be demonstrated by using a simple model that presumes an all-equity firm whose investments are financed internally (Fama et al 1995 p 135). Dividends (D (*t*)) paid in year *t* equal to equity income (EI (*t*)) plus depreciation (DP (*t*)) minus investments (I (*t*)). This is illustrated in the equation below:

$$D(t) = EI(t) + DP(t) - I(t)$$

In case the expected depreciation and investments are somehow proportional to the expected equity income for any year $t+i$, then,

$$E_t D(t+i) = E_t[EI(t+i) + DP(t+i) - I(t+i)] = E_t EI(t+i)(1+k_1-k_2)$$

where k_1 and k_2 are the proportionality factors. Given r for the discount rate, we suppose for simplicity that r is constant in time. Then, the present value of the market equity at time t is the following:

$$ME(t) = (1+k_1-k_2)\sum_{i=1} \frac{E_t EI(t+i)}{(1+r)^i}$$

Hence, the book equity and market equity ratio would be:

$$\frac{ME(t)}{BE(t)} = (1+k_1-k_2)\sum_{i=1} \frac{E_t EI(t+i)/BE(t)}{(1+r)^i}$$

To interpret the result, we take the reciprocal of ME/BE. The above formula predicts that firms with higher expected earnings have a lower BE/ME ratios. This deduction is also corroborated by the empirical findings of Fama et al. (1995) performed on 6 portfolios composed of stocks of the NYSE, AMEX and NASDAQ during the years 1963- 1992.

2.6.3 P/E Effect

Studies have shown that the price earnings ratio of a firm has predicting power over the next period's returns. Basu (1977) tested the claim that low P/E ratio firms tend to outperform those with a high P/E ratio. His research included over 1400 industrial firms that were traded on the NYSE between September 1956 and August 1971. He computed the P/E ratio for each stock by taking the market capitalisation as the numerator, and the denominator was the reported annual earning before extraordinary items. He formed portfolios of low and high P/E ratios and observed their performance. During the 25 years, the portfolios with low P/E ratios earned higher returns than the high P/E securities. After adjusting for risk, results did not change. Basu further interprets the results as not an upfront failure of the efficient market hypothesis. Rather, he explains that P/E ratio information was not fully reflected in security prices in as rapid a manner as demanded by the semi-efficient form of EMH. These lags and frictions are part of market mechanisms. Indeed the P/E anomaly did exist in the period studied, however, transaction costs and taxes greatly hindered investors from yielding abnormal profits. Explanations to this anomaly highlight the exaggerated expectations of investors.

2.6.4 Small-Firm Effect

Relating to the January effect that was previously introduced, the small-firm effect seemed to accompany the January returns. Banz (1981) has done research in this field. His study on the common stocks of the NYSE aimed at finding empirical relationship between the return and the total market value. Results showed that smaller firms possessed higher risk adjusted returns, on average, than larger firms. This size effect has existed from the 1940s for about 40 years. It is still unclear whether size as such is responsible for the effect or whether size is just a proxy for one or more true unknown factors correlated with size.

2.6.5 Over and Under Reaction to Earnings

Amongst other anomalies observed is share price over and under reaction to earnings news. DeBondt and Thaler wrote on the issue in their publication in 1985. "Research in experimental psychology suggests that, in violation of Bayes' rule, most people tend to "overreact" to unexpected and dramatic news events." (DeBondt & Thaler 1985 p. 804) They researched data of the NYSE for the years 1926-1982 in an attempt to observe the over/under reaction hypothesis. Their first hypothesis postulated that extreme movements were followed by a reaction in an opposite direction reverting it towards the mean. This occurrence is called mean reversion. Their other hypothesis assumed that the more extreme the movement was, the stronger the mean reversion. DeBondt and Thaler classified stocks into two portfolios depending on their performance in the last 36 months prior to the initial point of the testing. This way the Winners and the Losers' portfolios were created. Comparing the performance of the two portfolios the authors found that the Losers outperformed the market by 19.6%, the Winners accordingly, underperformed the market by 5%, despite that the later group included riskier stocks. The results clearly abide by the overreaction hypothesis. The deviation of the two portfolios is asymmetric; the Losers deviate more upward than the Winners downward. The difference between the two portfolios was sizeable in the 2nd and 3rd years.

The concept of market betas arises. When taken into account, the different betas in the portfolios did not contradict the results, contrarily, they confirmed them. The previous Winners had large betas on average; thereby the previous Losers yielded higher returns while being less risky. Moreover, a clear January effect is detected in previous Losers' portfolios. This effect is coupled with a loss in Novembers and Decembers. This seasonality is faint in the case of previous Winners and even contrary in direction. A number of aspects of the results remain without satisfactory vindication; principally, the large positive excess returns earned by the loser portfolio every January. Surprisingly, the effect lasts as late as five years post portfolio formation.

2.6.6 Mean Reversion

In DeBondt and Thaler the hypothesis of investor over and reaction is related to the concept of mean reversion. It is a tendency of stochastic process to remain near, or veer towards a long-run average value. According to riskglossary.com, interest rates and implied volatilities tend to exhibit mean reversion, so do stock market returns. Figure 2 illustrates the difference between mean reverting and non-mean reverting behaviour. (Source: riskglossary.com downloaded 5th March, 2008)

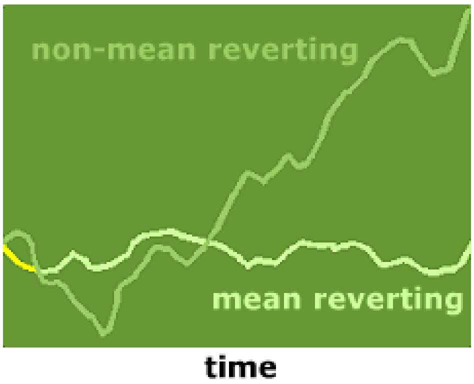


Figure 2 Mean reverting and non-mean reverting behaviour

The mean reversion model may be exploited to make extra gains. In general terms, the idea is that high or low periods in the stock market are only temporary. First, we identify a trading range for an instrument, and then compute the mean. Sophisticated calculations relate to assets and earnings of the firm. When the spot price in the stock exchange goes below the average price, the stock becomes attractive for investors who rush to place purchasing push to raise its price. When they over-react, the high priced stock is expected to fall. Eventually, prices will converge to the mean in the long-run. How long is the long-run? That is an issue open for argument.

Foster and Stine (2003) studied the incremental added-value of mean-reverting trading strategies. They introduce a test to determine whether a particular investment strategy can yield profits superseding returns of a buy-and-hold investment in the S&P index. They regress excess returns of the selected strategy against the excess returns from the buy-and-hold investment in the S&P index. The obtained t-statistic as well as the p-value of the intercept indicates whether adding a new strategy leads to a significant improvement in the performance of the portfolio. They adjust the p-values using the Bonferonni[5] corrections for multiple comparisons. If the regression intercept were statistically significant, then that means that the particular strategy did add value to the original strategy of buy-and-hold the S&P index. The concept behind this test is that a strategy that gives a positive mean return and is not too highly correlated to the benchmark index (S&P in this case) can be linearly combined with the index to obtain a better mean-variance return profile. Put simply, any strategy that proves to be an adequate supplement to diversify holdings in the benchmark index can add value.

Chua et al. (2004) examined this strategy on their mean-reverting yield-curve strategies. Their objective was to test the profitability of their strategies that build on the notion that the yield curve mean-reverts to an unconditional yield curve. The results showed that a number of these yield-curve trading strategies can yield high profits. This was especially true of the trading strategies that focused on mean-reversion of the yield spreads and curvatures. These strategies managed to substantially outperform two commonly used benchmarks of investing. When transaction costs were included in the model, profitability of the trades against the benchmarks dropped, yet significant results were sustained for some of these strategies. The authors suggested applying structured derivative trades that mirror the underlying cash flows in order to reduce the frequency of the trades, thus lower transaction costs considerably.

2.6.7 The Momentum Effect

Fama and French (1996) have also tested two versions of momentum strategies. DeBondt and Thaler's (1985) mean reversion anomaly is contradicted by Fama and French (1996). Fama and French tested their 3 factor model (see chapter 4.3) and found that portfolios

[5] In his article Hervé Abdi explains that when performing tests on a set of data, it is more likely to reject the null hypothesis when it is true *i.e.,* a "Type I" error. This is due to the logic of the hypothesis testing- when finding *rare* events, we reject H_0. The larger the number of tests, the more often we encounter *rare* events. This projects the false belief of thinking that there is an effect when there is none. Abdi says that this problem of *inflation* of the alpha level can be avoided by correcting the alpha level when performing multiple tests. Making the alpha level more stringent *i.e.,* smaller, will create less errors, but it may also make it harder to detect real effects.

formed based on past winner and losers demonstrated continuation or momentum rather than the contrarian effect of DeBondt and Thaler. A previous study by Jegadeesh and Titman (1993) corroborates the concept of momentum. The sample periods they use are the 1965–1989 period. The strategy they tested, that picks stocks according to their last 6-month returns and holds them for 6 months, realises a compounded on average excess return of 12.01% per year. The authors find further evidence indicating profitability of their strategies is not due to systematic risk. Moreover, test results also indicate that abnormal profits are not attributed to lead-lag effects resultant from delayed stock price adjustments to universal factors. When compared to the CAPM benchmark, results confirm the momentum effect as being quite large and reliable.

In their answer to the mean reverting theory, the authors suggests that “the evidence of initial positive and later negative relative strength returns suggests that common interpretations of return reversals as evidence of overreaction and return persistence (i.e., past winners achieving positive returns in the future) as evidence of underreaction are probably overly simplistic. A more sophisticated model of investor behaviour is needed to explain the observed pattern of returns. One interpretation of … [their] results is that transactions by investors who buy past winners and sell past losers move prices away from their long-run values temporarily and thereby cause prices to overreact.” (Jegadeesh et. al. 1993 p. 90) This interpretation is consistent with other studies that explored the implications of the so-called "positive feedback traders" on market price.

Jegadeesh and Titman also look at the question why it is possible that the market underreacts to information about the short-term prospects of firms but overreacts to information about their long-term prospects. They bring up two reasons for “The nature of the information available about a firm's short-term prospects, such as earnings forecasts, is different from the nature of the more ambiguous information that is used by investors to assess a firm's longer-term prospects. The evidence in this paper does not allow us to distinguish between these two hypotheses about investor behaviour.” (Jegadeesh et. al. 1993 p. 90)

2.6.8 Other Anomalies

Other anomalies include the following.

Standard & Poor's Index Effect

Financial literature refers to the Standard & Poor's index effect as being observable as soon as a company's inclusion in the index is announced. The perception was induced by the increased demand from index fund partakers for the stocks involved in index composition changes. Kappou, Brooks and Ward (2007) studied the S&P 500 inclusions and examined the impact of potential overnight price adjustments after the announcement of an S&P 500 index change. The authors found evidence of "a significant overnight price change that diminish[ed] the profits available to speculators although there … [were] still profits available from the first day after announcement until a few days after the actual event." (Kappou et. al. 2007 p. 21)

Initial Public Offerings

The IPO effect was studied as it appeared to cause an anomaly. Knopf and Teall studied the IPO underpricing anomaly in an attempt to explain returns of the initial trading day. They found evidence in support of the asymmetric information theories of IPO underpricing. When the investor bought the listed shares in the last period of the offering day, he would realise below average returns on the long-run. This effect was present even when companies were segmented according to industry or according to capitalisation. The underperformance was compared to several benchmark indexes. The reasons are that on the day of the offering prices jump, and buying at the closing price will yield worse than other investment opportunities. The companies that enlist to the stock exchange are usually over-valued, because it is not worth offering under-valued shares. Moreover, it is not uncommon to window-dress financial statements of companies prior to being listed for an IPO. For instance, they defer certain costs in order to improve their net profit and report more favourable results. Further explanation refers to the loss of efficiency when a company's division loosens control over its achievement.

Closed-end funds

A closed-end fund is a financial instrument that is listed on a certain day, at a certain quantity, and then initial offering takes place in a secondary market typically from a broker. The value of the investments in the fund, and the premium (or discount) placed on it by the market are what determine the price of a share in a closed-end fund. The total value of all the securities in the fund is divided by the number of shares in the fund. This is called the net asset value (NAV). The market price of a fund share is frequently higher or lower than the NAV. When the fund's share price is higher than NAV it is selling at a premium; conversely when it is lower, it is selling at a discount to the NAV.

Closed-end fund shares, in contrast to open-end funds, are priced by the market, often substantially diverging from the NAV of the fund assets. Open-end funds are only available for buying and selling at the close of business each day, at the calculated NAV, and for which orders must be placed in advance, before the NAV is known.

The market prices of closed-end funds are often ten to twenty percent different than the NAV while the value of an exchange traded fund would only very rarely differ from the NAV by more than one-fifth of a percent. Malkiel (1977) says that this is in startling contrast to securities' market efficiency. He develops some theoretical principles concerning the valuation of shares of closed-end investment companies. His conclusion is that while the structure of discounts can be partially explained on the basis of theoretical principles, the sizes of the discounts are far larger than warranted. The years he tested from 1970 to 1990 demonstrated an average discount ranging from 5% to 20%. Malkiel made several conclusions as to what justifies these premiums and discounts. "Discounts were related to unrealized appreciation (during the period when funds had unrealized appreciation) and to distribution policy with respect to capital gains, as well as to portfolio policies concerning investing in letter stock and foreign securities." (Malkiel 1977 p.857) However, the general explanation he gives is a psychological one: generally, closed-end companies sell at discounts because they must be bought through brokers- brokers who are not enthusiastic to sell them. The problem stems from investor habits whereas investment funds are not all that popular. It is unlikely to occur to the mind of the average investor to *buy* such a fund. Rather, the public is *sold* fund shares by the brokers or salesmen. Brokers prefer to sell those types of securities that earn them the largest amount of commission. Closed-end funds include way less commission than other financial products. Moreover, it is very likely for such a sale to be a one-time deal as the investors are even less likely to trade closed-end as they do with ordinary shares. Malkiels on the other hand explains, that this is still not justifiable reason for the closed-end funds to be discounted to this extent, and thereby the current mispricing should provide individual investors great opportunities. It seems likely, that the pricing of closed-end investment-company shares does illustrate an example of a market imperfection in the valuation of capital assets.

Weather

The weather anomaly is not related to weather derivatives, contrarily, it is concerned with the direct relationship between investment ambiance and meteorological factors. The empirical investigation of Saunders in 1993 revealed the effect of weather on human (investor) behaviour. He tested the null hypothesis that stock prices from exchanges in New York City have not been systematically affected by local weather. Saunders showed that there is a negative connection between the cloudy appearance and the yield of stock markets. His conclusion was that "the discovery that the weather in New York City has a long history of significant correlation with major stock indexes supports the view that investor psychology influences stock prices. The causal linkage in these correlations is strongly supported both by the extensive experimental and survey literature indicating that weather influences mood." (Saunders 1993 p.1344) The establishment of causal direction between a temporal, economically insignificant, local, mood influence and asset prices explains some of the surprisingly large economic impact this anomaly instigates. The empirical findings of Saunders support arguments for "the inclusion of economically neutral behavioural variables in models of asset-pricing and cast doubt on the hypothesis that security markets are entirely rational." (Saunders 1993 p.1345)

2.7 Causes of the Anomalies

The observed anomalies induced the search for causes that would explain the behaviour of asset mispricing. The most common reason brought up for explaining the year-end effect was tax-loss selling. This was relevant to countries were income from trading is not exempt from taxation. Investors with losing positions at the end of the year would close their positions to realise their losses before the tax year, thus save on their payable tax. At the turn of the calendar year, they would buy back the relatively cheap assets and reopen their positions. Once this was done by a considerable number of investors, the selling power at the end of December caused prices to fall even more, and the purchase rally in the first days of January accounted for the extra profits.

Window-dressing is the result of the rush of fund managers to appear the performance of their portfolios in their best shape before publishing their reports. Their end of year premium and their managers' satisfaction depends on the performance of the funds. This provokes the face-painting of portfolios. The easiest way is to sell distressed stocks and buy in "star" instruments regardless of which industry they are in. In the reports, investors will be shown the "good choice" of portfolio composition the fund manager has made. Another explanation related to this point is the uneven distribution of information. Traders can build on information revealed by firms, and only then, they are able make decisions as opposed to those in connection with such information.

This is what is called trading against insiders. Because it is riskier, it commands a risk premium. This idea means that insiders sell in December and buy back in January; investors who have no insider knowledge take up opposite positions. Thus, the January effect culminates in higher rewards.

Finally, in this context it is imperative to mention the joint hypothesis problem. The joint hypothesis denotes that the market efficiency hypothesis is coupled with the model of market equilibrium which is the price setting mechanism. The notion of market efficiency cannot be rejected without an accompanying rejection of the model of market equilibrium and this caused much discontent amongst researchers.

The reason for rejecting the hypothesis stems from the cost of information, and this makes the efficient market hypothesis impossible to exist in reality. Prices cannot perfectly reflect the information which is available, since if they did, those who spent resources to obtain it would receive no compensation, leading to the conclusion that an informational efficiency of markets is impossible. On the other hand, the degree of market inefficiency tempts investors to gather and analyse information, hence non-degenerate market equilibrium will arise only when there are sufficient profit opportunities, in other words rewards to compensate investors for the costs of trading and information-gathering. “The profits earned by these industrious investors may be viewed as economic rents that accrue to those willing to engage in such activities." Lo and MacKinlay (1999), pages 5-6

"*When you expect things to happen - strangely enough - they do happen.*"

J.P. Morgan

3 Behavioural Finance

J.P. Morgan was referring to a phenomenon called self-fulfilling prophecy that can be best explained by behavioural finance. What cannot be explained by theory is attributed to the unique psychology of the investors. Financial theory presumes rational behaviour from market participants. Yet some decisions are made quickly, with no sufficient time or information. Investors are also driven by their desires, emotions and fears. This is what led to the emergence of behavioural finance (BF). Some of the explanations BF gives to the nature of price movements include the following:

Gambler's Fallacy: Investors are inclined to expect reversal to occur more frequently than they actually do. People who have poor understanding of the nature of the random processes tend to fall for the gambler's fallacy.

Selective thinking is when investors believe what they want to believe and take notice of market signs that are favourable to them, ignoring undesirable evidence in order to explain a certain trade strategy or a belief.

The weekend effect or the Monday effect is based on the observation that share prices tend to start off on a Monday morning where they left off on Friday, thus not taking into account the money-value of the 2 days of the weekend. This anomaly connotes that Friday returns have proven to exceed those of Monday.

Window dressing is a last minute make-up that portfolio managers give to their assets before the quarterly or year-end reports. They sell off losing instruments or event buy into "hot" sector despite the fund being specialised in something else and investor are mislead to the real holdings of the portfolio. The aim here is to produce desirable funds in the reports.

Finally, the hindsight bias is an ever truthful phenomenon. It gives a more predictable view of upcoming events than they really are. Knowing the outcome of events encourages overconfidence in investors.

Proponents of behavioural economics note that financial models often fail to predict outcomes of the real world. Behavioural insights try to correctly predict some outcomes in cases where traditional models failed.

4 Anomalies: Premium or Inefficiency

Market mechanisms of reacting to new information are what determine the informational efficiency of that particular market. The promptness of share prices in reflecting additional information before it is exploited by arbitrageurs is what makes a market efficient. Rather, this process ought to be instantaneous. If not so, this deficiency will lead to mispriced shares that are a source of abnormal profits.

The degree of efficiency describes the extent of information prices reflect. Taking the thought of market efficiency a step further, the only way for a market to be completely efficient is by allowing time for investors to react to new knowledge, thus new transactions will shift prices accordingly. This mechanism will, in turn, ensure sustaining market efficiency. Yet there are always ‘early-birds’ whose trading initiates price correction, and they are the ones who will make extra profits.

Does this mean that it is inevitable for market movers to make abnormal (risk-adjusted) profits, as the market functions this way? This premium is the payment for the so-called ‘early-birds’ for researching and looking out for such opportunities.

How can data-mining be this rewarding when market transparency and speed of information is facilitated by modern telecommunication? In reality, these abnormal profits exceed any justified premium. Here Lakonishok, Shleifer and Vishney (2004) maintain that this is evidence for market inefficiencies and analysts tend to rely far more on past performance in forecasting the future. He says that future performances of gaining shares tend to be assessed more positively than of those shares that are losing on the market. This is called long memory in the time series.

Fama[6] defends the efficient market theory and rebukes that while EMH lacks a sound alternative theory, a replacing supposition would include explanations of long-term market over-reaction and under-reaction to events as explanations to the causes of market anomalies. On the other hand, Fama argues that chances of over-reaction are about as likely to occur as chances of under-reaction; this is, in turn, consistent with efficient market hypothesis.

4.1 A Test to the CAPM

The Capital Asset Pricing Model supposes that all available investment is represented by a market portfolio that mainly includes stocks. This is in itself a limitation in the CAPM as it is nearly impossible to accrue all available market investments into an index. Moreover, the market index defined in theory actually is far from any representation of the real market index. But for the sake of simplification, we shall consider the market index, the BUX as the reference investment portfolio. The model states that an asset's return is worth as much as the risk free (r_f) investment's projected returns are, plus beta (β) times the market risk premium ($r_m - r_f$).

$$r_i = r_f + \beta(r_m - r_f)$$

The market risk premium is the extra return an investor can expect over the riskless bonds, in exchange for bearing risk. This is market risk that is a diversified portfolio's probability of bad performance or default. The market does not reward systemic risk, as it can be diversified away.

In a quarter of a century that witnessed the CAPM's success, empirical evidence bolstered the model. Gaining shares all had high betas, which meant that they moved with the market, and low beta shares, accordingly were the worst performing shares. Moreover, investments made in highly volatile instruments would make one expect high yields. Even

[6] Fama, E.: Market Efficiency, Long-Term Returns, and Behavioral Finance; *J Fin Econ* (1998): p. 283-306

such strategies turned out to be rewarding only when the betas of the underlying instruments were high.

Cochrane (1999) examined 10 portfolios of shares traded on the NYSE that were sorted by size according to market capitalisation. There was an extra portfolio for corporate bonds and another for long-term government bonds. He found there to be a difference in their excess returns. Excess returns refer to returns beyond the risk-free bonds. Large shares had lower average returns and smaller shares had higher average returns. He also noticed a large spread between treasury bills and share portfolios. The portfolio average returns were plotted against their betas, and the relationship would nicely fall on the CAPM generated regression. One portfolio, however, showed a higher return than the model would predict. And this was the portfolio encompassing the small firms. The deviation being statistically significant required an explanation. Small firms are riskier; they are expected to yield higher returns, but what about the excess returns not explained by the CAPM. This was the much talked about “small-firm effect” that was introduced.

In figure 3, the average returns versus betas on the NYSE value-weighted portfolio for ten size-sorted stock portfolios, a portfolio of government bonds, and another for corporate bonds. The sample period was 1947–96. The black line draws the CAPM prediction by fitting the market proxy and Treasury bill rates and the coloured line draws the CAPM prediction by fitting an OLS cross-sectional regression to the displayed data points. The small-firm portfolios are at the top right. Moving down and to the left, one sees increasingly large-firm portfolios and the market index. The points far down and to the left are the government bond and Treasury bill returns. (Source: Cochrane 1999 p.39)

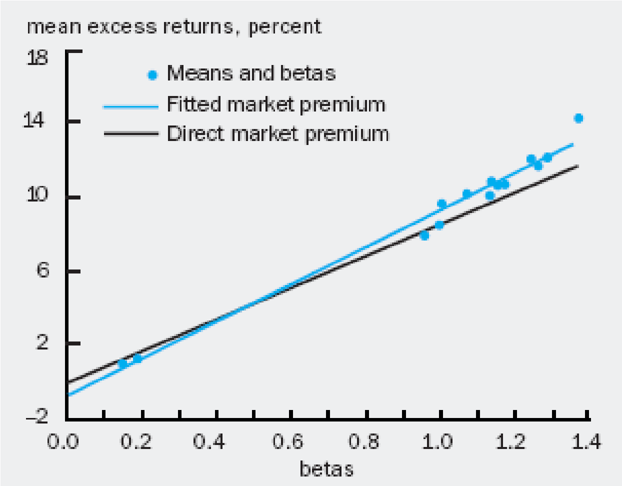


Figure 3: CAPM mean excess returns plotted against beta.

4.2 Multiple Factors

With hindsight, it is hard to explain the success of the CAPM for so long. It painfully lacked so many aspects of the real market, that its simple approach was marginalised from the outset. Since the times of Merton in the early 1970s, asset pricing theorists visioned the need of factors, or sources of price risk beyond the performance of the market portfolio. The CAPM uses a time-series regression to measure beta, which quantifies a portfolio's tendency to move with the market as a whole. Multifactor models extend this theory. They use a time-series multiple regression to quantify an asset's tendency to move with multiple risk factors F_A, F_B, etc.

An important handicap of the traditional CAPM model is that it assumes that investors live only off their investments, which constitutes that they are not affected directly by job market recessions. This is not the case in the real world. The average investor does have a job. For most of the players on the market, their aggregate monthly or yearly income is a sum of their wealth and their earnings. Important events like recessions hit the job markets and those who do not lose their jobs earn less and witness a shortfall in their bonuses. Few people make money during recessions. With this in mind, I bring in the example of two stocks A and B. Both have the same sensitivity to market movements, i.e. they have the same betas. But B does well during recessions while the other does not. Cleary, B will be preferred by investors as it will compensate their losses on their other income during bad times. If most investors think the same way, they bid up the price of B, or they will be willing to hold it at a lower average return. In the same manner, the instrument A that does worse during recessions will be sold cheaper or it must offer a higher average return for investors who are willing to hold it. We conclude that pro-cyclical instruments that perform well in booms but defect in busts will have to offer higher returns that the counter-cyclical instruments, regardless of their market beta. Therefore, another dimension of risk co-variation with recession periods will become a factor in asset pricing.

Added to this, we can bring up other inputs of the asset pricing formula that strongly correlate with the returns of investment portfolios. In broad terms, investors are willing to reward assets that outperform others especially during bad periods. This is particularly true as recessions are the times when we most need our investments to perform well to compensate other losses incurred. This involves investor preference to sacrifice part of their expected returns in exchange for assets that do well in recessions. This simple analysis sheds light on the second factor in the asset pricing factor model. Consumption or marginal utility is an apt proxy for measuring recessions. The population reduces its consumption when their income diminishes or when the projected future returns on their investments lessen. Low consumption thus indicates bad times when investors most likely want their investments to perform well and would be willing to pay for that compensation. Regrettably, relating asset returns to consumption data is a part of finance yet to be researched in greater depth. None the less, I find consumption to be a good logical indicator of what factors we should be looking for.

Empirical evidence examined more direct factors relating to asset returns. By and large these include the CAPM. At its core, the capital asset pricing model measures the sensitivity of the asset return to the market portfolio's returns. Investors are discontent if the market is in a downfall. In addition, factors that influence investors' non-capital gains, mainly salaries, are also important. The slope of the yield curve of stock or bond returns is a determining factor as well. These factors relate to average consumption. For instance, if the market as a whole declines, consumers lose money and will cut back on their consumption. Recessions witness the loss of jobs, and again a decline in consumption. Interest rate news act similarly as people who save everything for retirement will observe a drop in their wealth. This is what connects the predictability of returns and the presence of additional risk factors for understanding the cross-section of average returns.

An additional factor can be a factor-mimicking portfolio. Sometimes, when our factors are ‘unobservable’ we can construct a portfolio with the same features using enough securities. The new portfolio is sensitivity only to movements of that particular factor it wishes to mimic.

It is imperative that the risk factors that we wish to use to explain the movement of future returns affect the average investor. Envisage the case of an event that would make investor A better off, while making investor B worse off. In this case, A will buy the instrument that is affected by the event (or factor) and B will sell it. Thus, they will shift the risk of the factor while the price or expected return of the instrument will remain unchanged. For a factor to influence prices or expected returns, it must affect the average investor, so investors collectively bid up or down the price and the expected return of assets that covary with the event rather than just transferring the risk without affecting equilibrium prices. Inspired by this broad direction, empirical researchers have found quite a number of specific factors that seem to explain the variation in average returns across assets. Two important examples of such factors are size and book-to-market value ratio.

4.2.1 Market Capitalisation and the Value Premium

Size and book-to-market value ratio are market factors that underwent thorough empirical testing. Size is determined by the market capitalisation of the company (price times shares outstanding). Value was measured by the book value to market value ratio. When the book equity to market equity ratio (BE/ME) is high, the stocks of the company are referred to as **value stocks**. Conversely, low book equity to market equity identifies **growth stocks.** The logic behind this is that higher returns are compensation for higher systematic risk. Fama and French suggest that book-to-market and size are “proxies for distress and that distressed firms may be more sensitive to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable." (Fama and French 1996 p 58)

Possible explanations for the high discount rate assigned to small capitalisation and high BE/ME firms cause debate amongst experts. The traditional explanation for these observations advocated by Fama and French (1993, 1996) is that the higher returns are compensation for higher systematic risk. Fama and French (1993) explain that BE/ME and size proxy distress and that troubled firms are more susceptible to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable. This means that investors are willing to give up on some expected return in exchange for investments that are resilient to market turbulences. This causes the premium in small size and high BE/ME stocks.

Lakonishok et. al. (1994) propose that the high returns associated with high BE/ME stocks are generated by investors who incorrectly extrapolate the past earnings growth rates of firms. They suggest that investors are overly optimistic about firms which have done well in the past and are overly pessimistic about those that have done poorly.   The authors also suggest that growth stocks are more glamorous than value stocks and may thus attract naive investors who push up prices and lower the expected returns of these securities.

Value stocks have market values that are small relative to the value of assets on the company's books. Both value stocks as well as small capitalisation stocks have high average returns. Large and growth stocks are the opposite of small and value stocks which seem to have unusually low average returns. The idea that low prices lead to high average returns is natural. High average returns are consistent with the CAPM, if these categories of stocks have high sensitivity to the market, i.e. high betas. However, small and especially value stocks appear to have abnormally high returns even after accounting for market beta. Conversely, growth stocks do systematically worse than their CAPM betas suggest. Cochrane (1999) demonstrates this value-size puzzle by sorting stocks into portfolios based on size and book-to-market ratio. The highest portfolios have three times the average excess return of the lowest portfolios, and this variation has nothing to do with market betas.

To understand the real, macroeconomic, aggregate, non-diversifiable risk that is proxied by the returns of the high BE/ME and small capitalisation portfolios, Fama and French (1995) note that the typical value stock has a price that has been driven down due to financial distress. The stocks of firms on the verge of bankruptcy have recovered more often than not, which generates the high average returns of this strategy. This observation suggests a natural interpretation of the value premium: in the event of a credit crunch, liquidity crunch, or flight to quality, stocks in financial distress will do very badly, and this is precisely when investors least want to hear that their portfolio is losing money.[7]

4.3 Three Factor Model of Fama and French

Fama's contribution is crowned by his work with his colleague French[8] with whom he devised the three-factor model that extends the single market premium factor of traditional asset pricing theories. In their work, they show that sensitivity to size and value provides an adequate model for share price movements. The first factor is denoted as SMB (small minus big) which is the difference between the returns on diversified portfolios of small capitalisation stocks and a portfolio of large stocks constructed to be neutral with respect to book equity to market equity (BE/ME). The second factor is HML (high minus low) is the difference between the returns on diversified portfolios of high and low book equity to market equity shares constructed irrespective to size. The betas are evidently slopes in the regression. Their model is described in the equation below:

$$R_t^i - R_t^f = \alpha_i + \beta_{im}(R_t^m - R_t^f) + \beta_{iSML} SMB_t + \beta_{iHML} HML_t + \varepsilon_t^i$$

R_i is the return on asset *i*, R_f is the risk-free interest rate, and R_m is the return on the value-weight market portfolio.

[7] The individual risk of firms is not counted as a risk factor as such distress is idiosyncratic and can be eliminated by diversification, only aggregate events that average investors care about can result in a risk premium.

[8] Fama, E.; French K.: The Capital Asset Pricing Model: Theory and Evidence; The Journal of Economic Perspectives, Vol. 18, No. 3. (Summer, 2004), pp. 25-46

Table 4 shows the summary statistics of the three factors' regression on the July 1929 to June 1997 time-series. Fama and French split the sample on July 1963 to test whether the later period is unusual. The two sub periods are equal in length, 34 years. (Source: Fama and French 2000 p. 6)

	$R_M - R_f$	SMB	HML	S/L	S/M	S/H	B/L	B/M	B/H
7/29–6/97: 816 months									
Ave	0.67	0.20	0.46	1.05	1.30	1.53	0.89	1.04	1.34
Std	5.75	3.26	3.11	7.89	7.49	8.38	5.65	6.19	7.41
t(Ave)	3.34	1.78	4.24	3.80	4.96	5.21	4.52	4.78	5.16

Table 3: Summary Statistics for Monthly Percent Three-Factor Explanatory Returns

Rf is the one-month Treasury bill rate from Ibbotson Associates. *Ri* is the value-weight return on all NYSE, AMEX, and NASDAQ stocks with book equity data for the previous calendar year. At the end of June of each year *t* (1926 to 1996), stocks are allocated to two groups (small or big) based on their June market capitalisation, ME (market equity worked out by stock price times shares outstanding), is below or above the median for NYSE stocks. Stocks are allocated to three book-to-market equity (BE/ME) groups (L, M, or H) based on breakpoints for the bottom 30 percent, middle 40 percent, and top 30 percent of the values of BE/ME for the NYSE stocks in their sample. Six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed as the intersections of the two size and the three BE/ME groups. Value-weight monthly returns on the portfolios are calculated from July of year t to June of *t+1*.

The average value of the market premium (R_m-R_f) for the full 68-year sample period is 0.67 percent per month (t-statistic = 3.34) which is about 2.4 standard errors from zero. This strong market premium in returns in not surprising. There is also a reliable value premium in returns. The average HML return for the full July 1929 to June 1997 is 0.46 percent per month (t-statistic = 4.24). The size effect however is modest in comparison with the previous results. The average SMB return for July 1929 to June 1997 is 0.20 percent per month (t-statistic = 1.78). Perhaps the reason for this is that SMB is neutral with respect to BE/ME because small stocks tend to have higher BE/ME than big stocks, and a size premium that is not neutral with respect to BE/ME in part reflects the value premium in returns.

4.4 Characteristics Model of Daniel and Titman

The three factor model confirms that firm sizes and book-to-market equity ratios are both highly correlated with the average returns of stock market instruments. The Fama and French explanation of their model associates the size and value characteristics with returns. They explain that the characteristics are proxies for non-diversifiable factor risk, and that the sensitivities of underlying stocks with the factors (factor betas) directly influence returns. Daniel and Titman rebut this idea. In their article in 1997, they provide evidence that the return premia on small capitalisation and high book-to-market stocks does not arise because of factor betas. They voice the role of the characteristics rather than the covariance structure of returns that appear to explain the cross-sectional variation in stock returns.

Abundant evidence exist that cross-sectional pattern of stock returns can be explained by characteristics such as size, book-to-market ratios, leverage, past returns, and dividend-yield among others. Fama and French's examination of these variables simultaneously concludes that the cross-sectional dispersion in expected returns can be satisfactorily explained by two of these characteristics, namely: size and book-to-market ratio. Beta, the risk measure in the traditional capital asset pricing model explains very little of the cross-sectional variation in expected returns once size is taken into account. In order to determine expected returns, Daniel and Titman suggest a model of the "Return Generating Process Firm characteristics" (Daniel et. al. 1997) rather than factor loadings.

Their characteristic-based pricing model, in contrast to the factor pricing model, assumes that high book-to-market stocks realise a return premium that is unrelated to the underlying covariance structure. As in Fama and French's model, covariances are stationary over time and can be described by a factor structure. Here, a time-invariant *J*-factor describes the variance-covariance matrix of returns is assumed. (Source Daniel and Titman 1997 p9)

$$\tilde{r}_{i,t} = E[\tilde{r}_{i,t}] + \sum_{j=1}^{J} \beta_{i,j} \tilde{f}_{j,t} + \tilde{\varepsilon}_{i,t} \qquad \varepsilon_{i,t} \sim N(0, \sigma_{ei}^2), \quad f_{j,t} \sim N(0,1)$$

where $\beta_{i,j}$ is the loading of firm *i* on factor *j* and $\tilde{f}_{j,t}$ is the return on factor *j* at time *t*. However, in contrast to the previous models, factor loadings do not describe expected returns. Instead, it is assumed that expected returns are a function of the observable, slowly varying firm attribute or characteristic $\tilde{\theta}_{i,t}$: (source Daniel and Titman 1997 p10)

$$\mathrm{E}[\tilde{\mathrm{r}}_{\mathrm{i,t}}] = \mathrm{a} + \mathrm{b}_1 \cdot \tilde{\theta}_{\mathrm{i,t-1}}$$

As in the factor model, the innovations in θ are negatively correlated with the returns on the stock, but θ is not directly related to the loadings on the distressed factors. What is unique about the characteristics model is that firms exist that load on the distressed factors but which are not themselves distressed, and therefore have a low θ and thus low returns and vice versa. If the characteristics model holds, then a series of negative shocks to a specific factor may be followed by some stocks that, despite their high loadings on that factor, are still not distressed. The factor model suggests that these firms should still earn the distress premium, because they behave like other distressed firms. In contrast, the characteristics model suggests their returns behaviour does not matter: if they are not distressed they will not earn the premium. This model implies that a clever investor can earn the book-to-market return premium without loading on any common factors.

The regression results for the characteristic-balanced portfolios of Daniel and Titman support these findings. Table 5 presents each of the coefficients and t-statistics from the following time-series regression of the zero-investment portfolio returns, described below, on the excess-market, SMB and HML portfolio returns:

$$R_{i,j,k} - R_f = \alpha + \beta_{Mkt} \cdot R_{Mkt} + \beta_{HML} \cdot R_{HML} + \beta_{SMB} \cdot R_{SMB}$$

The regressions are over the period July 1973 to December 1993. The left hand side portfolios are formed based on size (SZ), book-to-market (BM), and pre-formation HML factor loadings; their returns are calculated as follows. From the resulting forty-five returns series, a zero-investment returns series is generated from each of the nine size and book-to-market categories. These portfolios are formed, in each category, by subtracting the sum of the returns on the 4th and 5th quintile factor-loading portfolios from the sum of the returns on 1st and 2nd factor-loading portfolios. The first nine rows of the table present the t-statistics for the characteristic-balanced portfolio that has a long position in the low expected factor loading portfolios and a short position in the high expected factor loading portfolios that have the same size and book-to-market rankings. The bottom row of the table provides the coefficient estimates as well as the t-statistics for this regression for a combined portfolio that consists of an equally-weighted combination of the above nine zero-investment portfolios. (Table below: source Daniel et. al. 1997 p18)

Char Port		Char-Balanced Portfolio: t-Statistics				
BM	SZ	$\hat{\alpha}$	β_{Mkt}	β_{SMB}	β_{HML}	R^2
1	1	1.43	−0.43	−2.69	−9.21	31.48
1	2	0.50	0.18	1.98	−8.99	31.48
1	3	−0.48	−1.62	−2.52	−8.57	27.11
2	1	1.37	−2.02	1.31	−7.13	18.43
2	2	2.12	−0.99	−2.07	−4.69	10.96
2	3	0.79	−1.41	−2.34	−3.96	9.11
3	1	2.53	−5.30	−0.48	−8.00	23.36
3	2	2.01	−2.30	−0.63	−4.52	8.58
3	3	1.08	−1.30	−2.36	−4.98	12.39
Combined portfolio		0.354	−0.110	−0.134	−0.724	41.61
		(2.30)	(−3.10)	(−2.40)	(−12.31)	

Table 4: Regression Results for the Characteristic-Balanced Portfolios

These are "characteristic-balanced" portfolios, since both the long and short positions in the portfolios are constructed to have approximately equal book-to market ratios and capitalisations. In the model, where no transaction costs are assumed, such a portfolio construction costs nothing initially.

The characteristic-based model predicts that the average return from these zero cost characteristic-balanced portfolios should be indistinguishable from zero. The results reported in Table 5 reveals that all but one of the as from the time-series regressions of the nine individual characteristic-balanced portfolio returns on the factor returns are positive, and three of the nine have t-statistics above two which is consistent with the characteristic-based pricing model but inconsistent with the factor pricing models.

The latest study on this topic by Daniel and Titman (2001) replicated the methodology of their 1997 tests on the Japanese market from 1975 to 1997. The authors maintain that Japanese stock returns are even more closely related to their book-to-market ratios than their U.S. counterparts. The tests reject the Fama and French three-factor model, but fail to reject the characteristic model. The results, however, may be subject to sample bias and might not be applicable to other markets. Daniel et. al. (2001) conclude that this is a question that stimulates further research.

5 Empirical Findings of the Budapest Stock Exchange

Historical data was gathered from portfolio.hu and a check was done to confirm its validity by comparing it to data gained from the Budapest Stock Exchange website. In order to compare the two data series, I used a macro that highlighted differences in share prices for the same dates. The portfolio.hu data proved to be incomplete in several cases; therefore, I relied on the bet.hu website for data download. I worked with 23 shares (16 of which compose the BUX basket), distributed variously between A and B category shares all traded on the Budapest Stock Exchange between September 2003 and September 2008. Using the VLOOKUP function in MS Excel, daily closing prices and dividends were adjusted according to trading days for each share. The task was to collect information on a specific date for all the shares on one row. In this process, I obtained numerous blank cells, which indicated unavailable data. Later I had trouble coping with missing data.[9]

5.1.1 Calculating beta and mean return

For each share, the daily return was calculated using the formula:

$$r_i = \sqrt[T-t]{\frac{P_T - P_t + Div_{t \to T}}{P_t}}$$

where P_T is the share price on day T, the dividend is the amount paid between t and T, and P_t is the share price in the period preceding T. In my calculations, I presumed that investors follow a buy-and-hold strategy for one year, and then they realise gains or losses. Therefore, the time elapse between t and T is 365 calendar days. Then the mean, standard

[9] To handle N/A data, one method is not to include them in calculations, or another method is by replacing them with the mean. I chose the first option.

deviation and variance of these returns were given for each share. I also produced daily returns for the BUX index in the same way, to serve my calculations as a market proxy. Each share's daily yields' covariance with the market yields was worked out. The market beta for each share was obtained by the formula:

$$\beta_{im} = \frac{\text{cov}(r_i, r_m)}{\sigma^2_{market}} = \frac{\rho_{i,m} . \sigma_i . \sigma_m}{\sigma^2_{market}}$$

Results are summed up below. Table 17 highlights the returns on the stocks, and their empirical betas obtained using the method explained above, and where available, I included the beta given by Reuters for the 16 shares that make up the BUX index. Here, I used the longest possible time-frame that extended from January 1996 – November 2007.

	OTP	Richter	MOL	M-telekom	Egis	Any	Danubius	Econet
Stock return	0.756	0.338	0.523	0.407	0.221	0.929	0.295	-0.050
Empirical beta	0.371	0.503	0.388	0.595	0.594	-0.009	0.671	0.184
Reuters beta	1.050	0.790	1.210	0.880	1.120		0.430	0.750

	Emasz	FHB	Fotex	Pplast	Phylaxia	Raba	Synergon	TVK
Stock return	0.337	0.775	0.208	-0.026	-0.165	-0.239	-0.084	0.256
Empirical beta	0.323	0.109	0.578	0.564	0.298	0.286	0.417	0.518
Reuters beta	0.640	0.880	0.880	0.140	0.680	0.310	1.000	

Table 5. Returns of the 16 BUX constituent stocks, their betas calculated using yearly yields projected on 1 day, and their Reuters beta. Calculation period 1996 – 2007

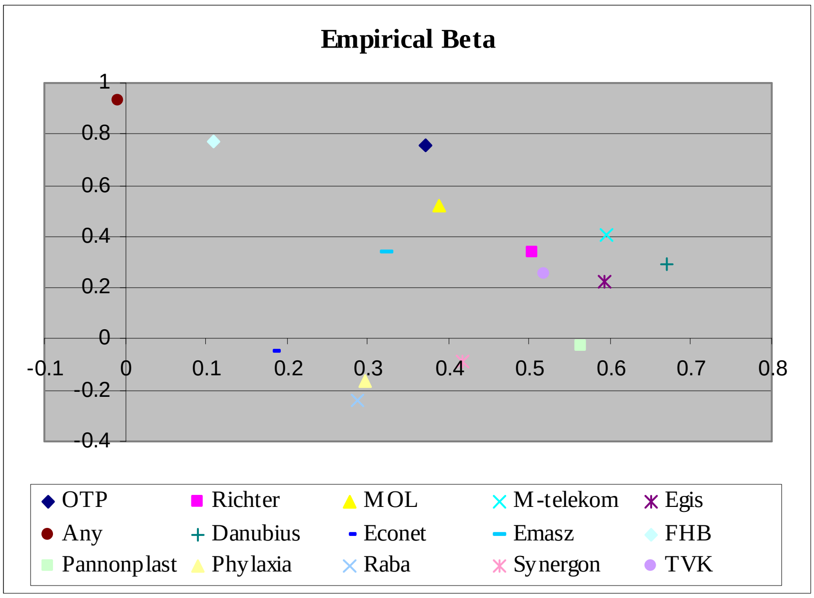


Figure 4: Empirical beta for BUX components, calculation period 1996 -2007

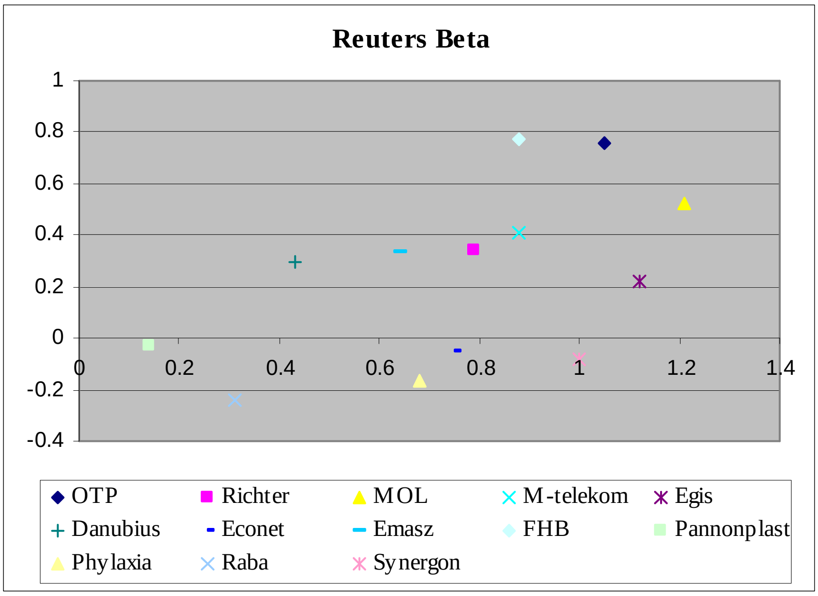


Figure 5: Reuters beta for BUX components, calculation period 5 years

I figure that using 12 years to calculate a beta may be irrelevant as the Hungarian capital market, as well as Hungarian currency went through immense changes since 1996. Table 18 depicts the same results as above using a shorter time-series from September 2004-March 2008 highlighting all 23 shares.

	Danubius	Econet	Egis	Fotex	Linamar	MOL	M-telekom	OTP
Stock return	0.916	0.205	0.346	0.864	0.718	0.741	0.574	0.653
Empirical beta	0.282	-0.117	0.365	0.317	-0.115	0.297	0.788	0.847
Reuters beta	0.430	0.750	1.120	0.880		1.210	0.880	1.050

	Pannon	Raba	Richter	Synergon	TVK	Zwack	Csepel	Ehep
Stock return	0.349	0.202	0.242	0.754	0.585	0.997	0.634	0.996
Empirical beta	0.296	-0.411	0.157	0.008	0.544	0.000	0.756	0.000
Reuters beta		0.310	0.790	1.000				

	Elmu	Exbus	Forras/oe	Gardenia	Humet	Konzum	Phylaxia
Stock return	0.735	-0.621	0.948	0.121	0.228	0.795	0.043
Empirical beta	0.259	0.115	-0.025	0.151	-0.469	0.466	0.280
Reuters beta							0.680

Table 6: Stock returns, betas calculated using yearly yields projected on 1 day, Reuters beta. Calculation period September 2004 – Sept. 2008

Using information from the table above, figures 8 and 9 below show the betas plotted against mean returns for the 23 shares.

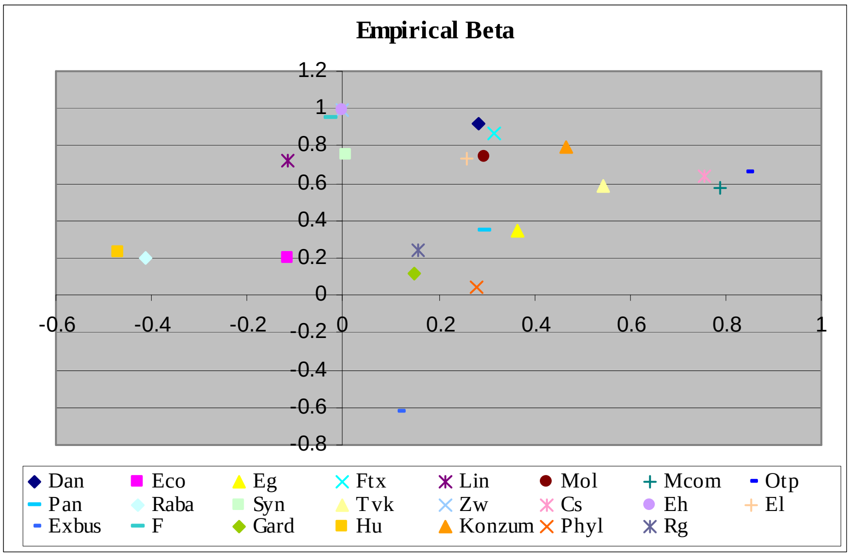


Figure 6: Empirical beta (x axis) graphed against stock return (y axis), period Sept. 2004 – Sept. 2008

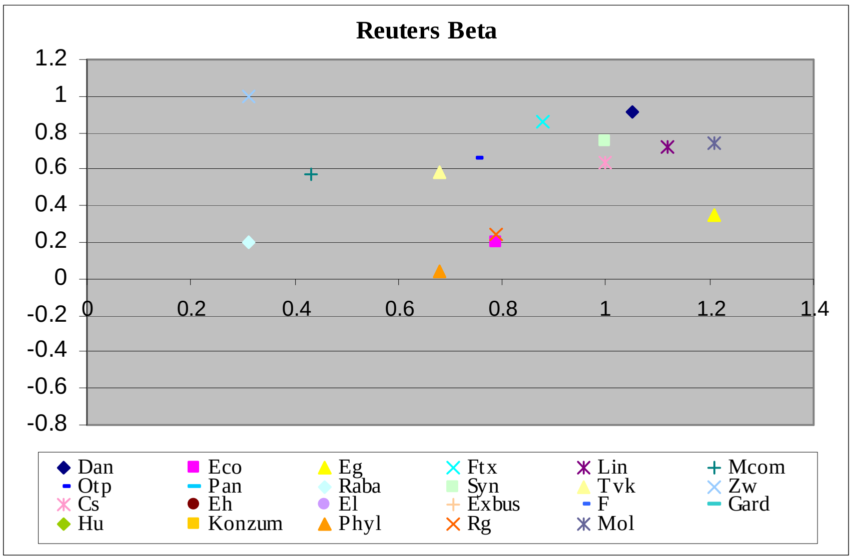


Figure 7: Reuters beta (x axis) graphed against stock return (y axis), period 5 years from 2007

In my model, I relied on the regression for obtaining the market beta. Reading Damodaran, I think I ought to apply other approaches as it is advisable to use a shorter period (e.g. 2 years) when calculating beta. Company profiles change over time and past covariance with the market might be irrelevant to the current situation of the company. I tried to check the so-called beta books, but unfortunately, Hungarian companies are not represented with a few exceptions. This is why I included beta obtained from Reuters.

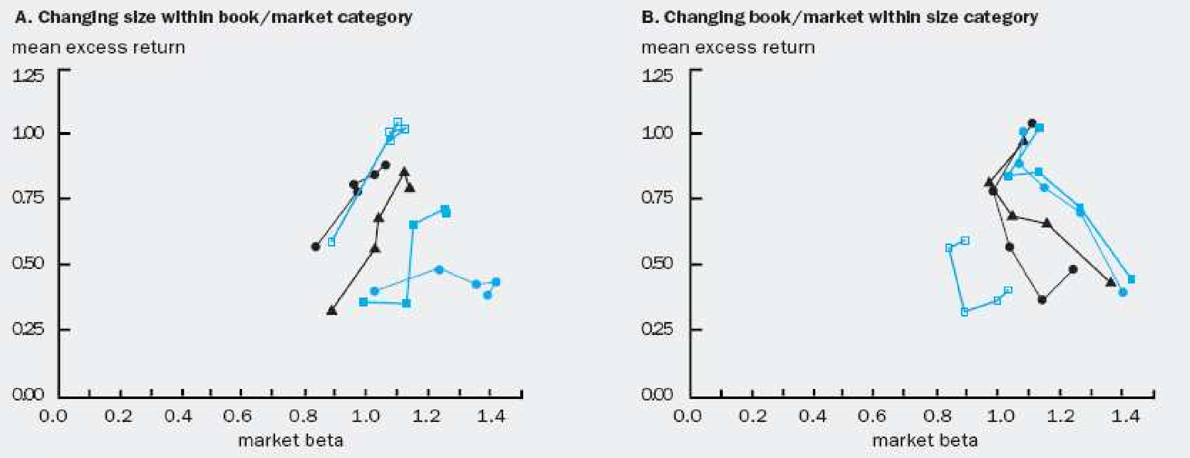
5.1.2 Forming Portfolios

In order to test the validity of the size and value factors in explaining returns on equity traded on the Budapest Stock Exchange, the gathered data from September 2003 to March 2008 of 23 stocks was mixed between A and B category stocks. The stocks were grouped into 6 portfolios according to size and book-to-market equity ratio. The small firms (S) were composed of companies with market capitalisation below the median irrespective of their book-to-market equity ratio, and the big firms (B) were those that were above the median. The high (H) book-to-market equity ratio firms were the top 30th percentile of the shareholder equity-to-market capitalisation ratio irrespective of size, the medium (M) category constituted the middle 40th percentile and the low (L) the lowest 30th percentile.

To take a look at how valid this grouping was I performed a hierarchical cluster analysis using the statistical analysis software SPSS, once according to equity capitalisation and the second time, according to book-to-market equity ratio, using between groups linkage and squared Euclidean distance. I also repeated the results using within-groups linkage and Euclidean distance. Results are best visualised using a dendrogram, this is shown in appendix 1. In reading the dendrogram, the result is normally taken at a distance between 10 and 15 on the dendrogram scale. The formed clusters match with the previous grouping made according to percentiles and median as in Fama and French.

Portfolios were formed at the beginning of each financial year, and regrouped accordingly every next January. The shares in the portfolios were value-weighted using their market capitalisation for weights, and categorised. The resultant 6 portfolios were the following: S/H, S/M, S/L, B/H, B/M, B/L. This meant that the first S/H portfolio contained shares that were small in size and with a high BE/ME. Appendix 2 shows the portfolio constituents for each year.

In Cochrane (1999) portfolios of different sizes within the same book/market category were connected. Figure 10 shows average returns versus market beta for 25 stock portfolios sorted on the basis of size and book/market ratio. The points are the same in both panels. In panel A, lines connect portfolios as size varies within book/market categories; in panel B, lines connect portfolios as book/market ratio varies within size categories. Variation in *size* produces a variation in average returns that is positively related to variation in market betas, as shown in panel A. Panel B connects portfolios that have different book/market ratios within size categories. Variation in book/market ratio produces a variation in average return that is negatively related to market beta. Because of this value effect, the CAPM is a disaster when confronted with these portfolios. (Source: Cochrane 1999 p. 41)



Notes: Average returns versus market beta for 25 stock portfolios sorted on the basis of size and book/market ratio. The points are the same as figure 3. In panel A, lines connect portfolios as size varies within book/market categories; in panel B, lines connect portfolios as book/market ratio varies within size categories.

Figure 8: Mean excess returns vs. market beta, varying size and book/market ratio

I wished to check whether this realisation is valid for our 23 Hungarian shares. I took the shares plotted in figure 8, and in an analogous way to Cochrane, I connected shares that are close in BE/ME to each other irrespective of size. The darker line represents firms that were the top 30th percentile BE/ME ratio, and therefore labelled as the high firms. The orange line connects the medium firms with the middle 40th percentile of BE/ME, whilst the bright yellow indicate low BE/ME firms with the lowest 30th percentile of book-to-market equity ratio. The lighter line shows firms with market capitalisation above the median, these are the big firms. Figure 11 clearly shows that variation in *size* produces a variation in average returns that is positively related to variation in market betas.

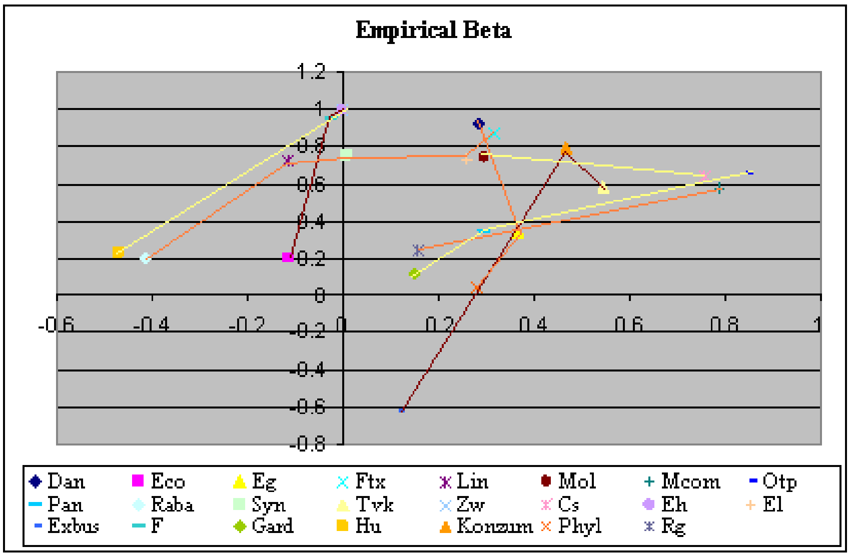


Figure 9: Varying size within book-to-market equity ratio groups.

In figure 12, I connected shares that are close in size to each other irrespective of BE/ME. The darker line represents firms that were below the median market capitalisation, and therefore labelled as the small firms. The lighter line shows firms with market capitalisation above the median, these are the big firms. It is clear, that variation in book/market ratio produces a variation in average return that is negatively related to market beta.

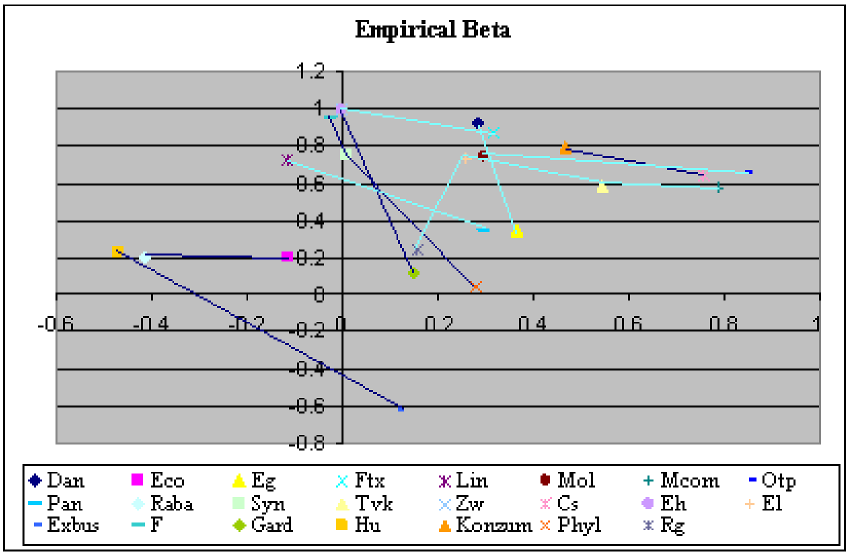


Figure 10: Varying book-to-market equity ratio within size groups

The multifactor model advocated by Fama and French (1993, 1996) explain these facts. The factors: market return, the return of small less big stocks (SMB), and the return of high book/market less low book/market stocks (HML) as three factors show, that variation in average returns of the size and book/market portfolios can be explained by varying loadings (betas) on the latter two factors.

5.1.3 The Factors: Market Premium, SMB and HML

The market premium is the excess return that investments yield over the risk-free return. I considered the BUX return as the market return (r_m) while the Hungarian 3 month reference rate as the risk-free rate (r_f) of government bonds. The problem arises that the market return does not includes all available investment opportunities, and as for the risk-free return, the inter-bank swap rates would provide a more dynamic indicator of market expectations. The difficulty of quantifying the former, and obtaining a time-series of the latter, unfortunately, confined me to only mentioning them. Figure 13 below illustrates the BUX yearly return and the 3 month government bond yield from February 1997 to March 2008.

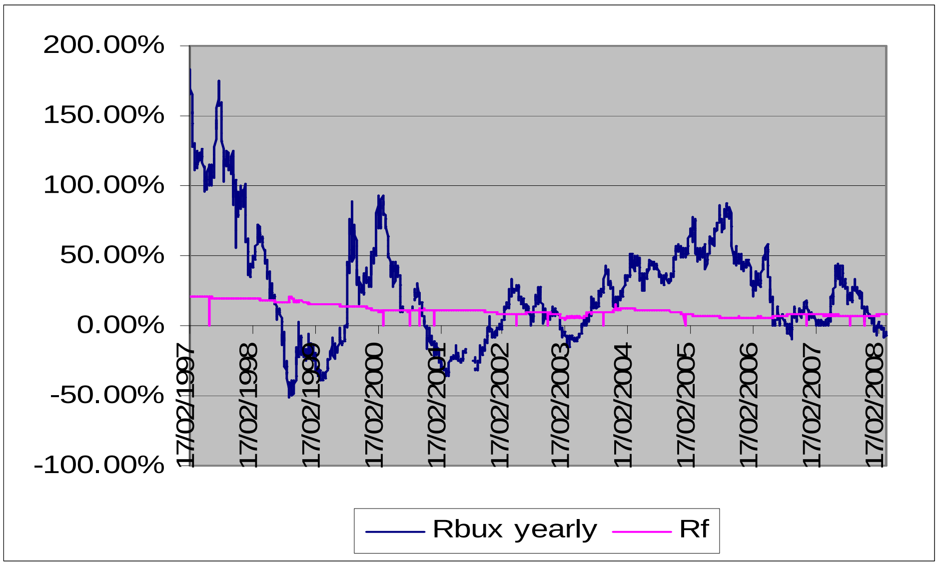


Figure 11: BUX yearly return and the 3 month government bond yield from February 1997 to March 2008

It is observed that there is a negative market premium several times in history as figure 14 shows.

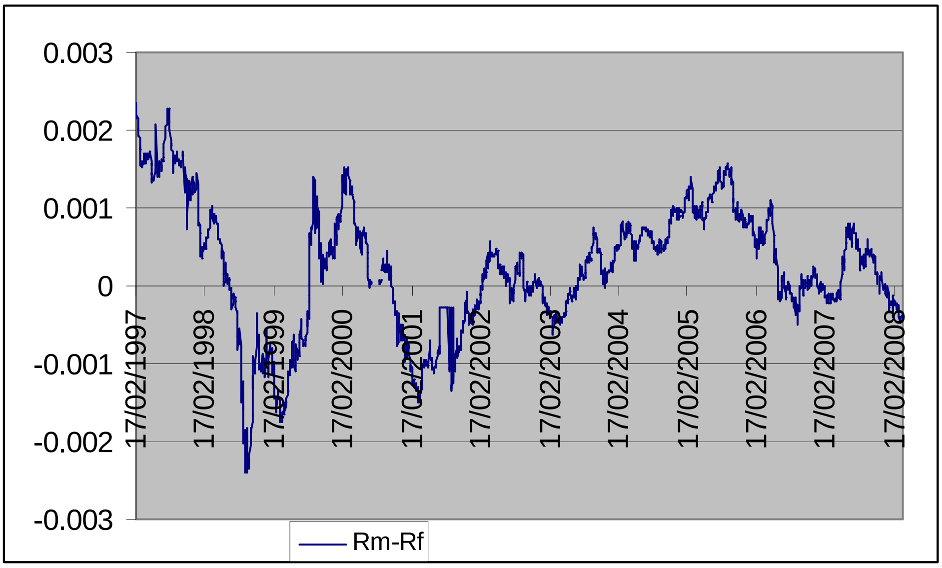


Figure 12: Market premium is shown by the excess return over the risk free rate.

In my calculations I used the yearly returns projected on a single day, using the equation:

$$r_i^{daily} = \sqrt[365]{r_i^{yearly}}$$

Damodaran Online suggests that Hungary use a market premium 5.99%. This information was updated in January 2008; however, I was unable to find historical market premia for Hungary. Therefore, I relied on empirical data.

The SMB and the HML factors were formed using the formulas of Fama and French. (1996) p392.

$$SMB = \frac{(S/L + S/M + S/H)}{3} - \frac{(B/L + B/M + B/H)}{3}$$

$$HML = \frac{(S/H + B/H)}{2} - \frac{(S/L + B/L)}{2}$$

The SMB factor shows the premium of the small capitalisation firms over the portfolio of big firms. The HML describes the premium of the high book-to-market equity ratio firms over the low ratio firms, in other words value less growth stocks.

In Fama and French (1996) the correlation between SMB and HML for the July 1929 to June 1997 period was 0.13. For the Hungarian market for the period 2004-2008 the correlation is -0.288 as shown in table 19. Thus, SMB indeed seems to provide a measure of the size premium that is somewhat free of BE/ME effects, and HML is a measure of the BE/ME premium relatively free of size effects.

	HML	SMB
HML	1.000000	-0.288366
SMB	-0.288366	1.000000

Table 7: Correlation matrix of the factors HML and SMB

I tested the HML and SMB factor for Granger causality. In the first case we cannot reject the hypothesis that SMB does not Granger cause HML at a 5% significance level, but we do reject the hypothesis that HML does not Granger cause SMB. Therefore it appears that Granger causality runs one-way from HML to SMB and not the other way. Table 20 summarises the results.

Pairwise Granger Causality Tests

Sample: 9/20/2004 3/31/2008

Lags: 5

Null Hypothesis:	Obs	F-Statistic	Probability
SMB does not Granger Cause HML	874	2.01188	0.07471
HML does not Granger Cause SMB		2.60463	0.02387

Table 8: Granger causality test for the factors HML and SMB

5.1.4 Fama's model tested on the Budapest Stock Exchange

Fama and French in their paper published in 1995 plotted the betas of share portfolios against their mean excess return. They propose a three-variable model to explain the movement of prices. Their renowned formula was (source Fama and French 1996 p. 55):

$$R_i - R_f = a + b(R_m - R_f) + cSMB + dHML + \varepsilon$$

Their regression fitted notably well. This induced several retests by other researchers including Cochrane (New Facts in Finance) who argues that the HML factor is not a solid explanation of the excess return of stocks (r_i-r_f) as high BE/ME indicates companies in distress. And it is more common for the distresses companies to bounce back than to default. This premium is therefore the price of survival. Fama and French revise their work in 1996 and comment the HML factor saying that "a substantial part of the premium is due to survivor bias; the data source for book equity … contains a disproportionate number of high-BE/ME firms that survive distress, so the average return for high-BE/ME firms is overstated." (Fama and French 1996 p57)

For the Budapest Stock Exchange's 23 firms, a summary table of the regressions of the three factors and a constant (C): (HML, SMB and Rm_Rf) are shown in table 21. Where the factors are significant on a 5% significance level, they are shown in bold letters. It is clear from the table that the size, the value and market premium factors work well for the period examined. On average, the SMB factor beta is 0,06 the HML 0,02 while the market factor has a beta of 0,29. This is interpreted as 1% point change in returns can be explained by beta times the given factor.

	Variable	Coefficient	Std. Error	t-Statistic	Prob.	R-squared
Csepel	**C**	0.589777	0.083756	7.041589	0.0000	0.278841
	HML	-0.112404	0.14719	-0.76367	0.4467	
	SMB	0.470486	0.116379	4.042709	0.0001	
	RM_RF	0.580364	0.096181	6.034102	0.0000	
Danubius	**C**	0.979557	0.013961	70.16223	0.0000	0.169405
	HML	0.117361	0.025139	4.668454	0.0000	
	SMB	0.018039	0.017086	1.055799	0.2914	
	RM_RF	0.273425	0.024761	11.04264	0.0000	
Econet	**C**	0.440438	0.029539	14.91049	0.0000	0.404035
	HML	0.753126	0.054385	13.84809	0.0000	
	SMB	0.791091	0.035179	22.48772	0.0000	
	RM_RF	0.301105	0.056859	5.295666	0.0000	
Egis	**C**	0.323306	0.02863	11.29273	0.0000	0.352909
	HML	0.221017	0.050472	4.379039	0.0000	
	SMB	-0.606565	0.034472	-17.5961	0.0000	
	RM_RF	-0.044635	0.05181	-0.861501	0.3892	
Elmu	**C**	0.68034	0.024578	27.68067	0.0000	0.226421
	HML	-0.081973	0.043109	-1.901532	0.0576	
	SMB	-0.364532	0.028896	-12.61523	0.0000	
	RM_RF	0.063817	0.048029	1.328701	0.1844	
Exbus	**C**	-0.491903	0.026517	-18.55067	0.0000	0.220354
	HML	0.191282	0.047021	4.068	0.0001	
	SMB	0.484169	0.03208	15.09243	0.0000	
	RM_RF	0.445035	0.050569	8.800487	0.0000	
Forras_oe	**C**	0.943952	0.011726	80.4988	0.0000	0.025713
	HML	-0.053201	0.020912	-2.544099	0.0111	
	SMB	0.038475	0.013995	2.749076	0.0061	
	RM_RF	-0.000312	0.021852	-0.014278	0.9886	
Fotex	**C**	0.937855	0.017417	53.84614	0.0000	0.135737
	HML	0.085885	0.030816	2.787016	0.0054	
	SMB	0.059029	0.020975	2.814239	0.0050	
	RM_RF	0.354849	0.031472	11.27492	0.0000	
Gardenia	**C**	0.169576	0.051089	3.319253	0.0010	0.108836
	HML	0.133069	0.088851	1.497656	0.1350	
	SMB	-0.377584	0.061752	-6.114509	0.0000	

	RM_RF	-0.07927	0.089246	-0.888222	0.3749	
Humet	**C**	0.224454	0.025137	8.929185	0.0000	0.568952
	HML	-0.347476	0.044671	-7.778609	0.0000	
	SMB	0.791583	0.030852	25.6573	0.0000	
	RM_RF	0.092363	0.044282	2.085805	0.0373	
Konzum	**C**	0.786754	0.039892	19.72202	0.0000	0.21806
	HML	-0.090905	0.073042	-1.244566	0.2144	
	SMB	0.294369	0.057623	5.108576	0.0000	
	RM_RF	0.470035	0.057301	8.202984	0.0000	
Linamar	**C**	0.664265	0.026104	25.44727	0.0000	0.353315
	HML	-0.627162	0.047659	-13.15926	0.0000	
	SMB	0.17287	0.032992	5.23973	0.0000	
	RM_RF	-0.132299	0.055699	-2.375244	0.0179	
	Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**R-squared**
Mol	**C**	0.645359	0.020963	30.7857	0.0000	0.31578
	HML	-0.497559	0.036956	-13.46358	0.0000	
	SMB	-0.39838	0.02524	-15.78336	0.0000	
	RM_RF	0.035944	0.037936	0.947497	0.3436	
Mtelekom	**C**	0.579918	0.022722	25.52178	0.0000	0.45536
	HML	-0.261916	0.040058	-6.538432	0.0000	
	SMB	-0.454327	0.027359	-16.60608	0.0000	
	RM_RF	0.487001	0.04112	11.84333	0.0000	
Otp	**C**	0.691461	0.02016	34.29819	0.0000	0.504452
	HML	-0.221531	0.035541	-6.233123	0.0000	
	SMB	-0.361232	0.024274	-14.88141	0.0000	
	RM_RF	0.607708	0.036484	16.65705	0.0000	
Pannon Energy	**C**	0.446192	0.03279	13.60751	0.0000	0.162063
	HML	-0.156804	0.05787	-2.709589	0.0069	
	SMB	0.389667	0.039313	9.912003	0.0000	
	RM_RF	0.570868	0.06022	9.479708	0.0000	
Phylaxia	**C**	0.143484	0.035509	4.040813	0.0001	0.10267
	HML	0.481215	0.062857	7.655686	0.0000	
	SMB	-0.062054	0.042972	-1.44404	0.1491	
	RM_RF	0.227353	0.064075	3.548234	0.0004	
Raba	**C**	0.330807	0.024251	13.64069	0.0000	0.570706
	HML	0.184613	0.042753	4.318104	0.0000	

	SMB	0.934285	0.0292	31.99598	0.0000	
	RM_RF	0.21231	0.043887	4.837621	0.0000	
Richter Gedeon	**C**	0.129809	0.033226	3.906793	0.0001	0.180322
	HML	-0.255864	0.058576	-4.368109	0.0000	
	SMB	-0.544314	0.040006	-13.60566	0.0000	
	RM_RF	-0.205513	0.060129	-3.41787	0.0007	
Synergon	**C**	0.718822	0.021758	33.03727	0.0000	0.232614
	HML	-0.470008	0.038357	-12.25337	0.0000	
	SMB	0.167931	0.026198	6.410147	0.0000	
	RM_RF	0.125849	0.039375	3.196188	0.0014	
TVK	**C**	0.701389	0.024631	28.47536	0.0000	0.38781
	HML	0.54939	0.043177	12.72412	0.0000	
	SMB	-0.255313	0.029665	-8.60648	0.0000	
	RM_RF	0.354323	0.04428	8.001918	0.0000	
Zwack	**C**	0.996578	6.56E-05	15199.28	0.0000	0.167957
	HML	-0.001131	0.000115	-9.81413	0.0000	
	SMB	-0.000477	7.84E-05	-6.086271	0.0000	
	RM_RF	0.000155	0.000118	1.306088	0.1920	

Table 9: Summary table of regression of the 3 factors on the 23 Hungarian shares

6 Limitations of the Study

Limitations of this study are numerous. Most importantly, the studies that I relied on for examining anomalies are outdated. The publication itself of an anomaly makes it disappear, as arbitrageurs rush to take advantage of whatever truth it held.

Another distortion to my study is that stock trading produces winners and losers. Only those losing stocks that recover are included in this study, but stocks whose companies default are neglected. This problem is not specific to this paper alone, but most published articles ignore defaulted companies.
This leads to theories that evolve around the certainty of market recovery.

A study of the Hungarian stock market seems ill-fated from the outset. The market lacks a history that would provide sufficiently long time-series of data to work with. Since the revival of the Budapest Stock Exchange in 1990 constant change of the stocks on trade characterised the stock market. The Hungarian market is also difficult to analyse because with the exception of the 4 major shares, it is not a liquid market in comparison to the developed stock markets. 80% of the BUX index is amassed in 4 shares, of which 2 accrue 60% the index. In addition, currently 41 shares are traded all together. This makes comparison to the US market unrealistic; therefore, drawing comparisons in stock behaviour and development is an unfortunate task. None the less, I found that transplanting Fama and French's findings to the Hungarian market did unleash insightful results.

To examine the reasons underlying the identified anomalies, we have to search the fundamentals. In this thesis, I merely identified some of the obvious explanations. Yet it might be of significance to search for the real question: to what extent are these market mispricings premiums? Do they compensate (il)liquidity, risk or are markets truly inefficient to uphold the efficient market hypothesis. Accepting the criticism or refuting it is also a very interesting topic to research study. Unfortunately, these questions are beyond the scope of this thesis.

7 Conclusion

In this thesis, I introduced asset pricing models. The birth of these models came hand in hand with a theory bolstering informational efficiency. We reviewed the extended literature that challenges the efficient market hypothesis. When market prices deviate from their theoretical pricing, they are dubbed as anomalies and investors rush to take advantage of the state of disequilibrium. Fama and French devised a multifactor model that is quite successful in incorporating anomalies in their asset pricing formula.

The researcher duo says, however, that these anomalies are actually premiums of distress. Their published papers have shown that characteristics of stocks such as market capitalisation and book-to-market equity are appropriate proxies for distress. Distressed firms may be more sensitive to certain business cycle factors, like changes in credit conditions, than firms that are financially less vulnerable. This means that investors are willing to give up on some expected return in exchange for investments that are resilient to market turbulences. This causes the premium in small size and high BE/ME stocks. Wile Fama and French propose that the two factors' loadings determine price movements, Daniel and Titman suggest that it is not factor sensitivities, but the characteristics themselves that are responsible for market yields.

The critics of the multifactor model rebuke that empirical testing was specific to the set of data examined by Fama; therefore its high precision in forecasting asset returns is not a coincidence. Others who place emphasis on the psychology of investors believe in the newly emerging behavioural finance. Eventually, investors are humans, with emotions and intuitions, and sometimes make irrational investments. This deems modelling of price movements to be far from precise.

The very debate over the explanations of anomalies gave me the impulse to test the relevance of the model on the Hungarian market. My approach was to apply the formula to the emerging Budapest Stock Exchange shares using an un-ambitious time series from September 2003 till March, 2008. Through empirical tests on the Budapest stock exchange, I find that the return of small and high BE/ME stocks does yield a premium. When regressed on the single stocks, The SMB and HML factors are positive on average, i.e. the three factor model produced significant loadings, indicating the model's validity for the period tested. On the other hand, the specifics of the Hungarian market suggest that excess returns account for liquidity premiums rather than compensation for distress.

In my opinion, it is easier to find explanations of past returns with the benefit of hindsight. Identifying mispricings in the spot market requires knowledge and hard work, and often times luck. This is why trading can be rewarding- or maybe not.

The question that remains open is an ongoing debate that financial literature is still unable to resolve: which aspects of the size and value factors are responsible for equity premia, is it the characteristic itself or the co-variation in returns related to size and book-to-market equity beyond the co-variation explained by the market return. I think this issue has opened questions that would quench the thirst of researchers for some time.

References

Abdi, H. (2007): The Bonferonni and Šidák Corrections for Multiple Comparisons; The University of Texas at Dallas; utd.edu/~herve/Abdi-Bonferroni2007-pretty.pdf downloaded on 20th March, 2008

Banz, R. (1981): The Relationship Between Return and Market Value of Common Stocks; Journal of Financial Economics, 9, 3-18

Basu S. (June, 1977): Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis; The Journal of Finance, Vol. 32, No. 3. pp. 663-682

Chua, C.T., Koh W., Ramaswamy K. (February, 2004): Profiting from Mean-Reverting Yield Curve Trading Strategies; http://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=ESAM04&paper_id=142 downloaded on 7th March, 2008

Cochrane, J. (1999): New Facts in Finance; Economic Perspectives, Federal Reserve Bank of Chicago, issue Q III, pages 36-58

Courtault J.M. Kabanov, Y., Bernard B., Crépel, P., Lebon, I., Le Marchand, A. (July 2000): Louis Bachelier on the Centenary of Théorie de la Spéculation; Mathematical Finance, Vol.10, No.3, 341–353 http://www.stochastik.uni-freiburg.de/bfsweb/LBachelier/mafi092XX.pdf downloaded on 14th March, 2008

Daniel K., Titman S. (1997): Evidence on the characteristics of cross sectional variation in stock returns, Journal of Finance, p. 52, 1-33.

Daniel K., Titman S., Wei J. (April 2001): Explaining the Cross-Section of Stock Returns in Japan: Factors or Characteristics? The Journal of Finance; Vol. LVI, No. 2

Davis, J., Fama, E., French, K. (February, 2000): Characteristics, Covariances, and Average Returns: 1929 to 1997; The Journal of Finance, Vol. 55, No. 1. pp. 389-406

DeBondt. W., Thaler R. (July, 1985): Does the Stock Market Overreact?; The Journal of Finance, Vol. XL, No. 3

Fama, E., French K. (1993): Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33; pp. 3-56

Fama, E., French K. (March, 1995): Size and Book-to-Market Factors in Earnings and Returns; The Journal of Finance, Vol. 50, No. 1. pp. 131-155

Fama, E., French K. (March, 1996): Multifactor Explanations of Asset Pricing Anomalies; The Journal of Finance, Vol. 51, No. 1. pp. 55-84

Fama, E. (1998): Market Efficiency, Long-Term Returns, and Behavioral Finance; Journal of Financial Economics 49 p.283-306

Fama, E., French K. (Summer, 2004): The Capital Asset Pricing Model: Theory and Evidence; The Journal of Economic Perspectives, Vol. 18, No. 3. pp. 25-46

Foster, D.P., Stine, R.A. (2003): Ponzironi Returns: How to distinguish a “con” from a good investment using only statistics; Working paper; The Wharton School, University of Pennsylvania

Haugen, R.(1999): The Inefficient Stock Market, What Pays Off and Why; Prentice Hall, Upper Saddle River, New Jersey

Jegadeesh N., Titman S.(March, 1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency; The Journal of Finance; vol. 48, No. 1, pp. 65-91

Kappou K., Brooks C., Ward C. (May 2007): The S&P 500 Index Effect in Continuous Time: Evidence from Overnight, Intraday and Tick-by-Tick Stock Price Performance; ICMA Centre, University of Reading, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=991858 downloaded 13th April, 2008

Knopf J., Teall J. (Fall 1999): The IPO Effect and Measurement of Risk; Journal of Financial and Strategic Decisions; vol. 12 no. 2

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

Lo; MacKinlay (1999): *A Non-Random Walk down Wall Street;* Princeton University Press, USA

Makara, T. (2006): Kötvénypiacok és kamatláb-derivatívok, Egyetemi jegyzet

Malkiel B. (June, 1977): The Valuation of Closed-End Investment-Company Shares; The Journal of Finance; Vol. 32, No. 3 p. 847-859

Malkiel B. (2003): A Random Walk Down Wall Street: the time tested strategy; W.W. Norton & Company Inc.; 500 Fifth Avenue, NY, 10110

Saunders E. (December, 1993): Stock Prices and Wall Street Weather; The American Economic Review; vol. 83, No. 5 p. 1337-1345

Singal V. (2006): Beyond the Random Walk: A Guide to Stock Market Anomalies and Low-Risk Investing; Oxford University Press, USA

Tímári, J. (2005): Hatékonyság és anomáliák a budapesti értéktőzsdén; www.bet.hu; Budapest

Tőkepiacről szólo törvény CXX/2001 § 199-205

http://www.riskglossary.com/link/mean_reversion.htm (downloaded on 5th March, 2008)

http://www.sec.gov/news/testimony/2006/ts092606lct.htm (downloaded on 15th February, 2008)

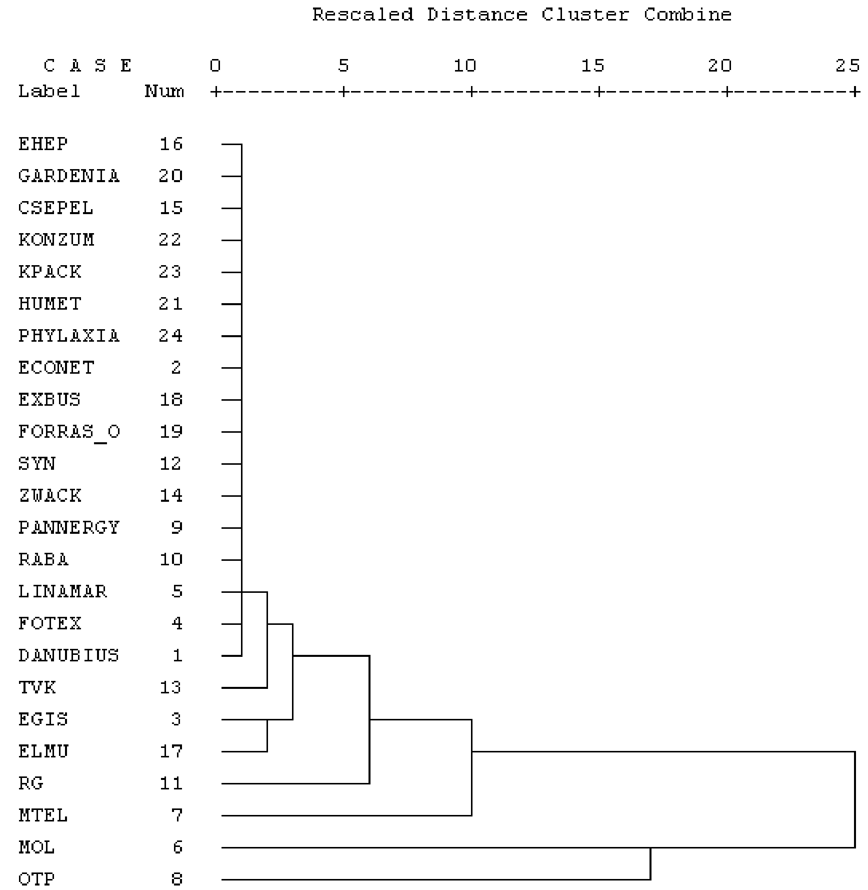
Appendix 1

Hierarchical cluster analysis according to equity capitalisation using within-groups linkage and Euclidean distance.

Dendrogram

* * * * * * H I E R A R C H I C A L   C L U S T E R   A N A L Y S I S * * * * * *

Dendrogram using Average Linkage (Within Group)

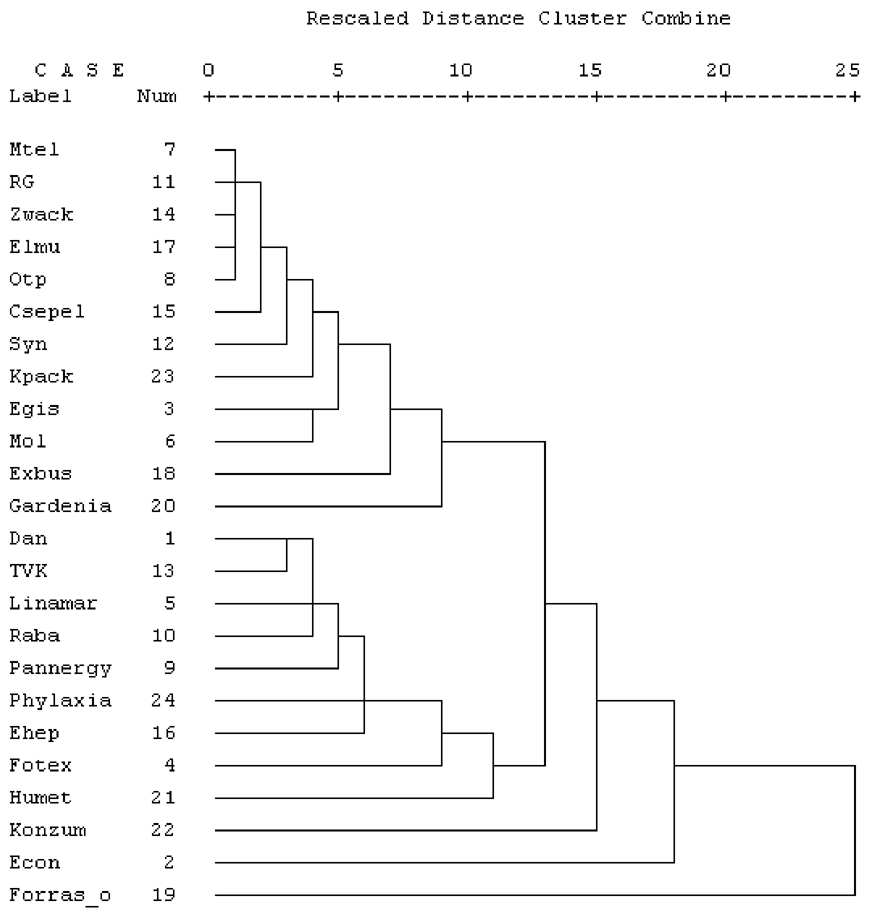


Hierarchical cluster analysis according to book-to-market equity ratio using within-groups linkage and Euclidean distance.

Dendrogram

* * * * * * H I E R A R C H I C A L   C L U S T E R   A N A L Y S I S * * * * * *

Dendrogram using Average Linkage (Within Group)



Appendix 2

2003				**2004**				**2005**			
SH	ECONET	BH	FOTEX	SH	ECONET	BH	FOTEX	SH	ECONET	BH	FOTEX
	EHEP				EHEP				FORRAS/OE		RABA
	FORRAS/OE				FORRAS/OE				HUMET		
	GARDENIA				HUMET				KONZUM		
	KONZUM				KONZUM				PANNERGY		
	PANNERGY				PANNERGY						
SM	HUMET	BM	DANUBIUS	SM	GARDENIA	BM	DANUBIUS	SM	CSEPEL	BM	DANUBIUS
	PHYLAXIA		EGIS		KPACK		EGIS		EHEP		EGIS
	SYN		LINAMAR		PHYLAXIA		LINAMAR		GARDENIA		LINAMAR
			MOL		SYN		MOL		KPACK		TVK
			OTP				RABA		PHYLAXIA		
			RABA				TVK		SYN		
			TVK								
SL	CSEPEL	BL	ELMU	SL	CSEPEL	BL	ELMU	SL	EXBUS	BL	ELMU
	EXBUS		MTELEKOM		EXBUS		MTELEKOM				MOL
	KPACK		RG				OTP				MTELEKOM
			ZWACK				RG				OTP
							ZWACK				RG
											ZWACK

2006				**2007**				**2008**			
SH	ECONET	BH	TVK	SH	EHEP	BH		SH	ECONET	BH	TVK
	EHEP				ECONET				EHEP		
	FORRAS/OE				EXBUS				EXBUS		
	KONZUM				FORRAS/OE				FORRAS/OE		
	PHYLAXIA				KONZUM				KONZUM		
	RABA			PHY	KPACK				KPACK		
SM	EXBUS	BM	PANNERGY	SM	HUMET	BM	DANUBIUS	SM	PHYLAXIA	BM	DANUBIUS
	HUMET		DANUBIUS		RABA		EGIS		RABA		EGIS
	KPACK		FOTEX				ELMU		SYN		ELMU
	SYN		LINAMAR				FOTEX				FOTEX
			MTELEKOM				LINAMAR				LINAMAR
			ZWACK				MTELEKOM				MTELEKOM
						TVK	PANNERGY				RG
SL	CSEPEL	BL	EGIS	SL	CSEPEL	BL	MOL	SL	CSEPEL	BL	MOL
	GARDENIA		ELMU		GARDENIA		OTP		GARDENIA		OTP
			MOL		SYN		RG		HUMET		PANNERGEY
			OTP				ZWACK				ZWACK
			RG								

6 portfolios formed each year according to size and book-to-market equity