Cross-sectional conditional risk return analysis in the sorted beta framework: A novel Two Factor Model

Petros Messis*, ***Antonis Alexandridis**, Achilleas Zapranis****

**Department of Accounting & Finance, University of Macedonia of Economics and Social Studies, Egnatia Str 156, 54006, Thessaloniki, Greece*
***School of Mathematics, Statistics and Actuarial Science, University of Kent, Canterbury, Kent, CT2 7NF, United Kingdom*

Abstract

This study examines the conditional relationship between beta and return for stocks traded on S&P 500 for the period from July 2001 to June 2011. The portfolios formed based on the Book value per share and betas using monthly data. A novel approach for capturing time variation in betas whose pattern is treated as a function of market returns is developed and presented. The estimated coefficients of a nonlinear regression constitute the basis of creating a two factor model. Our results indicate that the proposed specification surpasses alternative models in explaining the cross-section of returns.

Keywords: Cross-sectional regression; CAPM; S&P 500;

1. Introduction

This study aims at examining the conditional relationship between beta and returns using four well-known models (i.e. CAPM, Fama and French three factor model (FF3FM), Premium Labor- model (PLM), Arbitrage Pricing Theory (APT)) and a new one which in view of the strong evidence of betas instability, it tries to capture their time variation, considering their pattern as a function of market returns. Hence, the new model incorporates variables targeting to absorb the information conveyed by betas' variability. Our findings suggest that this specification surpasses alternative models, previously proposed in the literature, in explaining the cross-section of returns.

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) quantifies the risk return relationship, suggesting that the only relevant risk

* Corresponding author. Tel.: +30 2310891690; fax: +30 2310844536,
E-mail address: *pmessis@uom.gr* (P.Messis).

measure is the beta coefficient, which reflects the systematic risk. Due to the powerful and intuitively pleasing predictions (Fama and French, 2004) the model is still widely used by financial managers and investors to estimate the risk of the cash flow, the cost of capital and the performance of managed funds (Fletcher, 2000; Tang and Shum, 2003; Perold, 2004).

Fama and MacBeth (FMcB) (1973) conducted the first empirical examination regarding the validity of the CAPM. They found that on average a positive trade off exists between return and risk, leading to a conclusion in favour of the CAPM. However, empirical evidence in 1990s (e.g. Jegadeesh, 1992; Davis, 1994; Fama and French, 1996, Groenewold and Fraser, 1997) expresses doubts with regard to the validity of betas as risk measures, since their findings suggest that betas are not always significantly related to returns.

The limited empirical support found for the CAPM is interpreted in the literature either as evidence against the CAPM itself or as evidence that the testing methodology is not suitable. For the first case, the literature presents alternative tests of measures to the market premium factor suggested by the CAPM. For example, Banz (1981) finds that the size effect has a strong impact on stock returns, indicating that smaller firms have higher returns and thus higher betas. Similar findings are obtained by Zarowin (1990), Fama and French (1992) and Daniel and Titman (1997). Furthermore, book to market value and earnings to price ratios also appear to significantly influence the stock returns (Berk, 1995; Fama and French, 1996). Hence, stocks with high such ratios are followed by higher returns than stocks with low such ratios. Similar results have been found by Chan et al. (1991) for the Japanese market and by Levis and Liodakis (2001) for the UK market. Liquidity also appears to influence the expected stock returns as explained by Jacoby et al. (2000). Chen (1983) and Groenewold and Fraser (1997) conclude that the Arbitrage Pricing Theory (APT) of Ross (1976) outperforms the CAPM.

In addition, in the CAPM the beta coefficient is assumed to remain constant over ‘bull’ and ‘bear’ market conditions. However, Levy (1974) proposed that beta may differ with market conditions and inferences based on the stable nature of beta may be misleading. Fabozzi and Francis (1977) first tested the stability of betas over the ‘bull’ and ‘bear’ markets. Defining these specific conditions with three different ways, no evidence was found to support the hypothesis that the stock market affects betas asymmetrically. Clinebell *et al*. (1993) show that observed differences of beta coefficients between bull and bear market conditions are significant. Woodward and Anderson (2009) applying a logistic smooth transition market model (LSTM) for Australian industry portfolios report that bull and bear betas are significantly different for most industries while the transition between bull and bear states is rather abrupt. Wiggins (1992) finds the dual beta model of Fabozzi and Francis (1977) to explain better the portfolio returns formed by size, past beta, and historic return performance. Bhardwaj and Brooks (1993) conclude that there is not size premium when beta varies in up and down markets as small firm stocks underperform large firm stocks.

The FMcB testing methodology has been criticized for a number of reasons. Roll (1977) argued that the CAPM cannot be tested because the composition of the real market portfolio is not observed. Isakov (1999) reported that this particular methodology does not allow beta to appear as a useful measure of risk for two particular reasons. The first one relates to the fact that the model is expressed in terms of expected returns but tests can only be performed on realized returns. The second reason which closely relates to the first one is that the realized market excess return does not behave as expressed since it is too volatile and is often negative. Pettengill et al. (1995) proposed an alternative approach in which the excess market returns are separated into positive and negative, concerning that investors perceive the possibility of the risky assets' return being below the risk-free rate. However, the FMcB procedure is still used in most empirical studies (Fraser et al., 2004) for testing models in the cross-sectional framework.

The paper is organized as follows. Next section develops the methodology for the models' empirical examination, section 3 describes the data and reports the empirical findings, while section 4 concludes the paper.

2. Methodology

2.1 Capital Asset Pricing Model

The capital asset pricing model is a set of predictions concerning equilibrium of expected return on risky assets (Bodie et al., 2002). In the cross sectional context, the model states that differences in average returns depend linearly and solely on asset betas (Cuthbertson and Nitzsche, 2004). Cross-section tests are based on a two-stage procedure of FMcB. In the first step, a time series regression is performed for each security or portfolio *i* of the following form:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \tag{1}$$

where $R_{it} - R_{ft}$ is the excess return of asset *i*, $R_{mt} - R_{ft}$ is the market excess return, β_i is the systematic risk and a_i and e_{it} are assumed to be zero according to the model. In the second step, a cross-section regression is taken place between the sample average monthly returns (r_i) and the β_i 's estimates from the first step regression as equation (2) depicts:

$$E[r_i] = \lambda_o + \lambda_1 \hat{\beta}_i + \eta_i \tag{2}$$

In (2), λ_0 and λ_1 are constant across all assets. In addition, we expect that $\lambda_0 = 0$ and $\lambda_1 = \bar{R}_m - \bar{R}_f$ where the bars indicate the sample mean values. This is the unconditional CAPM, since conditional information plays no role in determining excess returns.

The conditional cross-section version of CAPM is as follows:

$$E\left[r_{it} \mid I_{t-1}\right] = \lambda_{0t-1} + \lambda_{1t-1} \hat{\beta}_{it-1} + \eta_i \tag{3}$$

In (3), I_{t-1} is the information set available at time *t* and λ_{1t-1} is the conditional market risk premium. The same assumptions for the conditional cross-section regressions hold for the remaingn models. All models are tested both unconditionally and conditionally.

2.2 Fama and French Three-Factor Model

The three-factor model suggested by Fama and French (1996) relates the expected return on a portfolio in excess of the risk-free rate, $E(R_i) - R_f$, to three factors. The first one is the excess return on a broad market portfolio (i.e. $R_i - R_f$), the second is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (i.e. Small Minus Big, SMB) and finally the third factor is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (i.e. High Minus Low, HML). Thus, the expected return on asset *i* is:

$$E[R_i] - R_f = \beta_i \left[E[R_m] - R_f \right] + s_i E[SMB] + h_i E[HML] \tag{4}$$

The terms $E[R_m] - R_f$, $E[SMB]$ and $E[HML]$ express expected risk premiums and the factor loadings, β_i, s_i, h_i are the slopes that come from the OLS time series regression (5) which constitutes the first step as above:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \tag{5}$$

We make the assumptions for a_i and e_{it} as in the previous section. Fama and French (1996) noted that the three-factor model has no foundation in finance theory, but it is merely a statistical model that summarises the empirical regularities that have been observed in US stock return (Gregory et al., 2001).

The cross-section regression is given by:

$$r_i = \lambda_o + \lambda_1 \hat{\beta}_i + \lambda_{SMB} \hat{s}_i + \lambda_{HML} \hat{h}_i + u_i \tag{6}$$

The intercept λ_o in the above equation should not be statistically different from zero while the factor risk premiums should be priced.

2.3 Premium-Labor model

The Premium-Labor model (PL-model) developed by Jagannathan and Wang (JW) (1996) introduces two additional variables. The first variable (premium) tries to capture the instability of the asset's beta over the business cycle. For this purpose, the authors use the spread between BAA- and AAA- rated bonds, since interest-rate variables are likely to be most helpful in predicting future business conditions (Stock and Watson, 1989). The second variable relates to the return on human capital. This variable is taken into consideration in order to measure the aggregate wealth, since the empirical failure of the CAPM has been attributed to the bad proxy of the market index (Roll, 1977). The return on human capital is assumed to be a linear function of the growth rate per capita labor income and hence this latter time series is used in the analysis. After estimating the betas (being orthogonal to one another) of the aforementioned variables in the time series context, the second step cross- section regression is as follows:

$$r_i = \lambda_o + \lambda_1 \hat{\beta}_i + \lambda_{prem} \hat{\beta}_i^{prem} + \lambda_{labor} \hat{\beta}_i^{labor} + v_i \tag{7}$$

This is the PL-model of JW, which is going to be used for empirical examination in the rest of the paper.

2.4 Arbitrage Pricing Theory (APT)

The APT developed by Ross (1976) attempts to overcome the anomalous empirical evidence that has plagued the CAPM (Lehmann and Modest, 1988). This equilibrium model generates fewer and more realistic assumptions than the CAPM. As a result, the model has attracted great attention, particularly as a 'testable' alternative to the CAPM (Parhizgari et al., 1993).

In APT, it is assumed that there are several factors generating returns for the securities (Bodie et al., 2002). The following equation illustrates the general form of the model:

$$R_i = a_i + \beta_{i,1}\Pi_1 + \beta_{i,2}\Pi_2 + ... + \beta_{i,k}\Pi_k + e_i \quad \text{for } i = 1,2,...,N \tag{8}$$

where R_i is the return of asset *i* while it is linearly related to a set of factors Π_j where $j = 1,2,...,k$. The beta coefficients show the sensitivity of the asset to each factor. Again, higher values of beta coefficients indicate greater sensitivity, whereas lower values indicate lesser sensitivity of the stock return to a particular factor. The last term of equation (8), e_i, is a random variable and it is expected to have an average value of zero over time (i.e. $E(e_i) = 0$) and to be uncorrelated across securities (i.e. $E(e_i, e_j) = 0$).

The cross-section regression of the APT is given by:

$$r_i = \lambda_o + \lambda_1\hat{\beta}_{1,i} + \lambda_2\hat{\beta}_{2,i} + ... + \lambda_k\hat{\beta}_{k,i} + \eta_i \tag{9}$$

The intercept λ_o in the above equation should not be statistically different from zero while the factor risk premiums should be priced. If there is only one statistically significant factor and that is the market risk, then the APT is equal to CAPM.

The main drawback of the APT is that it does not specify the number or type of factors that are important in determining security returns. Modern financial theory focuses upon systematic factors, as sources of risk, and suggests that macroeconomic variables systematically affect stock market returns. The inflation rate is the most common factor that influences the returns of a portfolio and is found to be significant for the US stock market (Chen et al., 1986) and for the UK stock market (Beenstock and Chan, 1988; Clare and Thomas, 1994). Similarly industrial production index, interest rate, retail index, money supply and fuel and material costs were found to be statistically significant in these studies.

2.5 A new approach: Two Factor Model

Two steps constitute the new approach we use here for capturing any variations in beta coefficients. In the first step, the beta coefficients from equation (1) are estimated. Using the standard OLS method and daily returns data of three years time interval[1], we estimate the first beta coefficient of period *t*. Next, a rolling regression is applied. More precisely in order to obtain the second value of beta, the first

[1] Daves et al., (2000) show that daily returns data of three years time interval give the best daily beta predictions.

observation is dropped and a new is added to the end of the sample. The procedure is followed for a five-year period estimating the respective betas of each day. Having about 1250 betas at hands, we rank them in ascending order relative to the market return on day t=1…1250.

Then, the averaged values of the estimated betas for each market return discrete interval are calculated. This ensures that the equality weights given at each observation capture any differences in each and every market condition. At the same time, we avoid any subjective bias at the selected market interval. The number of market return discrete intervals generally varies from period to period. It is determined by the extent to which a given period is more or less volatile. Being able to construct the used variables, a question arises regarding the form of beta coefficient as a function of R_{ms} (i.e. $\overline{\beta} = f\left(R_{ms}\right)$, (Faff and Brooks, 1998)). Lin et al., (1992) suggest that the beta mean fluctuates around an upward or downward parabolic trend pattern. Hence, we approach the functional form of $f(\cdot)$ by:

$$\overline{\beta}_i = \alpha e^{(bR_{ms} + cR_{ms}^2 + u_i)} \tag{10}$$

where α, b, c are the coefficients to be estimated, R_{ms} is the sorted market return, $\overline{\beta}_i$ are the average betas of stock i corresponding to each market return interval and u are the residuals. We do not make any assumption about the residuals distribution since we are interested only in the magnitude of the estimated coefficients.

Through linearization and assuming that beta coefficients are non-negative, as usually happens in financial contexts (Andersen et al., 2006), equation (10) can be written as:

$$\ln(\overline{\beta}_i) = \ln(a) + bR_{ms} + cR_{ms}^2 + u_i \tag{11}$$

If f is continuous in the interval $\left[R_{ms}^-, R_{ms}^+\right]$ and twice differentiable then $\frac{\partial \overline{\beta}}{\partial R_{ms}} = \overline{\beta}(b + 2cR_{ms})$ and $\frac{\partial^2 \overline{\beta}}{\partial R_{ms}^2} = 2c\overline{\beta}$. For $\overline{\beta} > 0$ and $c = 0$, f is linear while for positive and negative values of b, the function is increasing and decreasing respectively. If $c > 0$, f is convex as the second derivative is positive, while for $c < 0$, f is concave with negative second derivative.

We proceed to the construction of a two-factor model (hereafter TFM) where the variables are formed based on the b_coefficients of equation (11). It is expected that stocks with positive b_coefficients would give higher returns without an increase in the risk. The intuition behind this stems from the fact that at each state of market return nature the expected return of security *i* is higher. So, we could say that ‘Superior’ stocks are described by increasing beta coefficient as market return increases. The reverse holds for ‘Inferior’ stocks. A ‘Superior’ stock should include the characteristics that lead to higher returns than its competitors. For example, it could be a stock with relatively low leverage. Hence, in bad states of the world its beta coefficient would not increase as much as a stock with high leverage values (Jagannathan and Wang, 1996). Thus, the first variable named as ‘SMISI’ (i.e. Superior minus Inferior Stock Index) represents the difference in returns between the 30% of stocks with the highest b_coefficients and the 30% of stocks with the lowest b_coefficients. This variable aims at capturing the risk associated with ‘Superior’ and ‘Inferior’ stocks. The second explanatory variable, which we call it as ‘Neutral’ (Neutral Stock Index-NSI), is the remaining 40% of the stocks. The stocks that constitute the NSI have on average zero b_coefficients. This index is similar to the general index of S&P 500 if the assumption of constant betas coming from the CAPM holds. The time series regression is given by the following equation:

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it} \tag{12}$$

and the unconditional cross-section regression is given by:

$$r_i = \lambda_o + \lambda_{smisi}\hat{c}_i + \lambda_{nsi}\hat{n}_i + z_i \tag{13}$$

3. Empirical Results

3.1. Data description

The dataset used consists of securities traded on the S&P 500. The rate of return of each security, R_i, at time *t* is calculated as $R_{it} = P_{it} / P_{it-1} - 1$. The testing period spans from July 2001 to June 2011. The risk free rate is the 3-month US Treasury bill. In order to construct the variables used in the TFM we first employ daily observations for estimating the b_coefficients, as mentioned in the previous sections.

To include a stock in the ‘Superior’ or ‘Inferior’ portfolios for a given year, it must have statistically significant beta coefficients at least at 10% level (i.e.*t*-stat ≥ $|1.70|$) for all 5 previous years. This way, we ensure that each beta coefficient has explanatory power and that it can be used for estimation purposes. After forming the portfolios, monthly returns are constructed. The monthly return observations of the

FF3FM are retrieved from the authors' internet homepage[2]. For the PL-model we use the same variables as in JW. The bond yields of BAA and AAA used as the premium in the PL-model. Similarly, the per capita monthly income series was obtained from the Federal Reserve Bulletin published by the Board of Governors of the Federal Reserve System and was used as the labor variable. Following JW, the growth rate in labor income is computed as: $R_t^{labor} = [L_{t-1} + L_{t-2}]/[L_{t-2} + L_{t-3}]$, where L_{t-1} is the per capita labor income at month $t-1$, which becomes known at the end of month t.

In order to apply the APT, an arbitrary choice of macroeconomic variables has been made that influence the securities in the same degree, implying that all securities operate in the same economic environment and that the particular variables are important to the whole economy. However, some of them are similar to those employed by Clare and Thomas (CT) (1994). The selected macroeconomic variables that were used as independent variables in the first step regression (i.e. time series regression) are presented in table 1. The macroeconomic time series were obtained from the Federal Reserve Bank of St. Louis. Some of the time series such as output or inflation are used with one time lag in order to make these variables contemporaneous with series of portfolio returns (Chen et al., 1986; Clare and Thomas, 1994). For example, the announcement of January's inflation is done in February and hence investors revise stock prices accordingly in February.

Table 1: Macroeconomic variables

Variable	Symbol	Form	Series ID
Default risk	(BAA-LTGB)	FD	
Term structure	(LTGB-TB3M) (TS)	FD	
3 month treasury bill rate	(TB3M)	FD	TB3MS
Gold price	(GP)	FD	GOLDPMGBD228NLBM
Real retail sales	(RRS)	FDL	RRSFS
Industrial production	(IP)	FDL	INDPRO
Oil price	(OIL)	FD	MCOILBRENTEU
Unemployment	(UNEM)	FDL	UNRATENSA
M3	(M3)	L	MABMM301USM657S
Exchange rate	(EXR)	FDL	EXUSUK
Consumer price index	(CPI)	FDL	CPIAUCNS
Exports/Imports	(EXPIMP)	FD [L(Exp/Imp)]	BOPGEXP (BOPGIMP)
Yield on Long-term GB	(LTGB)	FD	10YCMR
Excess market return	(MR)	L	

Notes: The sample period is from July 1996 to June 2011. L, FD and FDL are for level, first differences and first differences of the log respectively for the selected time series. The series ID concern the identification code given by the Federal Reserve Bank of St. Louis.

The models are tested on two different portfolios sorted on the historical beta coefficients and the Book Value per share. The beta based portfolios are formed

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

following the standard FMcB methodology. The first five years of monthly observations (i.e. t-120,…,t-61) are used to estimate the betas for each security. Stocks with statistically significant betas higher than the 10% level were excluded from the sample. After estimating the stocks' β_i coefficients from equation (1), the stocks were ranked on the basis of estimated betas and were assigned to one of the ten portfolios. The first portfolio consisted of stocks with the lowest betas, while portfolio 10 consisted of stocks with the highest betas. This process was then repeated for each subsequent year in our data set. Hence, a time series of monthly returns from July 1996 to June 2011 for each of the ten portfolios were obtained. Next, the beta of each portfolio is estimated over the second period of 5 years (i.e. t-60,…,t-1) by regressing the realized portfolio returns on the market index. This is done in order to reduce the 'errors in variables' problem. This problem arises in empirical tests because beta estimates are used rather than true values. However, the errors in variables problem is reduced by grouping stocks into portfolios since portfolios' betas will be more precise estimates of the true betas than those for individual stocks (Clare and Thomas, 1994). The Book Value per share portfolios are formed every calendar year, starting in 2001, where we first sort firms into deciles based on their Book Value per share at the end of June. For consistency purposes, the beta portfolios have the same starting point every year. The Book-Value per share data were taken from Compustat.

Following Fraser et al. (2004), we repeat this procedure by updating the beta estimates on a monthly basis. Thus, time series of risk premiums of the models are generated. The test of significance of the risk premia is performed as in FMcB and CT as follows:

$$t_{\lambda} = \frac{\hat{\lambda}}{s\left(\hat{\lambda}\right)/\sqrt{n}} \tag{14}$$

In the above equation, $\hat{\lambda}$ is the mean value of the estimated risk premium, $s\left(\hat{\lambda}\right)$ is the standard deviation and n is the number of observations. The variables are priced over the estimation period at the 10 per cent level, when $|t|$ is greater than 1.30.

The relatively low number of available stocks at the very early stage of the sample could cause survivorship bias problems. To examine possible effects related to survivorship bias, we also form big and small sample portfolios. The small sample portfolios contain stocks that were used in the construction of the TFM. This is due to the fact that during the construction of the variables, the asked number of observations is higher (i.e. 8 years). The big sample portfolios contain stocks with statistically significant betas at least at the 10% level. Although the higher number of data availability the BVps portfolios are also formed from those stocks. For compatibility reasons between the two different kind of portfolios, we chose to reduce the number of stocks by 10% on average. Figure 1 depicts the number of shares contained in the two samples as well as the available data of the BVps.

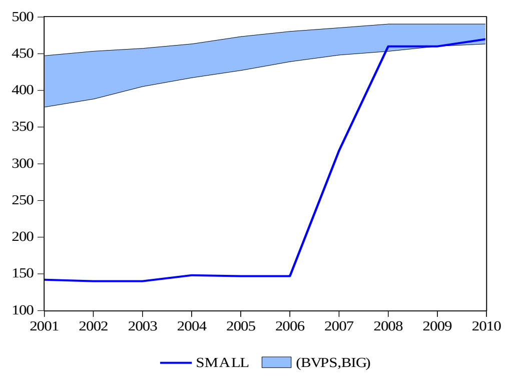

Figure 1: Number of shares in analysis

Tables 2 and 3 provide summary statistics of time series averages of portfolio returns for the two samples. For each portfolio, the tables show the mean monthly returns in excess of the 3-month Treasury bill, the standard deviation of the monthly excess returns and the *t*-statistics associated with the hypothesis of zero portfolio returns. Both tables exhibit the positive differences in returns between the lowest and highest BVps portfolios and highest and lowest beta based portfolios. The pattern of portfolio returns between the big and small samples looks similar. A deviation is observed between the 9^{th} and 10^{th} decile of small sample beta sorted portfolios.

Table 2: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using Book value per share and beta coefficients: 07/01-06/11, 120 Months, Big sample (429 shares on average per year).

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV per share	**Low**									**High**
Mean	1.91	1.42	0.99	0.95	1.06	0.97	0.92	0.63	0.79	0.34
Std. Dev.	6.20	5.37	5.03	5.44	5.86	4.87	5.41	5.56	5.31	6.25
t-statistics	3.38	2.89	2.15	1.92	1.98	2.18	1.87	1.24	1.64	0.60
Beta	**Low**									**High**
Mean	0.56	0.81	0.60	0.98	0.85	0.97	0.97	1.08	1.25	1.30
Std. Dev.	3.30	3.83	4.04	4.32	5.00	5.20	5.99	6.50	7.11	9.85
t-statistics	1.85	2.31	1.63	2.48	1.87	2.05	1.78	1.81	1.92	1.44

Table 3: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using Book value per share and beta coefficients: 07/01-06/11, 120 Months, Small sample (257 shares on average per year).

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV per share	**Low**									**High**
Mean	1.26	0.95	0.77	0.72	0.68	0.91	0.59	0.58	0.83	0.16
Std. Dev.	5.79	5.16	4.91	5.60	5.64	4.79	6.27	5.34	4.99	6.53
t-statistics	2.39	2.02	1.71	1.40	1.32	2.08	1.03	1.19	1.83	0.27
Beta	**Low**									**High**
Mean	0.42	0.61	0.49	1.01	0.66	0.83	0.79	0.77	1.13	0.73
Std. Dev.	3.58	3.72	4.04	4.30	4.78	5.46	6.40	6.84	7.41	9.76
t-statistics	1.27	1.80	1.34	2.57	1.50	1.66	1.36	1.24	1.67	0.82

The estimated average betas produced by CAPM are depicted in table 4. We do not find significant differences in betas within portfolios formed on BVps. However, this is not the case of beta-sorted portfolios as they range from a low of 0.47 to a high of 1.65. In addition, at both samples the slopes seem to follow identical pattern.

Table 4: The estimated average slopes for the portfolios formed using Book value per share and beta coefficients. Both samples are included.

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV ps Big	1.21	1.00	0.96	0.99	1.04	0.90	0.95	0.94	0.85	0.98
Beta Big	0.47	0.64	0.73	0.79	0.89	0.91	1.02	1.15	1.26	1.65
BVps Small	1.17	0.94	0.87	1.05	0.97	0.91	1.18	0.91	0.79	1.07
Beta small	0.48	0.57	0.68	0.69	0.79	0.95	1.17	1.30	1.40	1.82

In table 5 we present the findings of the existence of survivorship bias. Following the method of Banz and Breen (1986) we examine whether the returns over the 120 months for each portfolio are different. For brevity reasons, we report only the results of the Gibbons, Ross, Shanken (1989) test (hereafter GRS test) of the zero α's hypothesis. The table depicts that jointly α's are different from zero and statistically significant differences in returns between the big and the small sample exist. However, a more closely examination of portfolios indicates that only three out of ten and one out of ten cases are different from zero for the BVps and beta portfolios respectively.

Table 5: GRS test for testing the restriction that all ten alphas are jointly zero (constants in percent, std. errors in parentheses)

	Deciles										
	1	2	3	4	5	6	7	8	9	10	GRS test
BV per share	0.65	0.47	0.22	0.23	0.38	0.06	0.33	0.05	-0.04	0.18	3.37
	(0.23)	(0.15)	(0.15)	(0.16)	(0.16)	(0.14)	(0.19)	(0.11)	(0.14)	(0.11)	
Beta	0.14	0.20	0.11	-0.03	0.20	0.14	0.18	0.30	0.12	0.57	2.71
	(0.13)	(0.16)	(0.16)	(0.13)	(0.15)	(0.12)	(0.17)	(0.19)	(0.18)	(0.14)	

3.2. Unconditional and Conditional cross-section regressions

Panel A of table 6 depicts the evidence of the unconditional cross-sectional regressions from July 2001 to August 2011. It tries to identify risk premiums associated with factors other than market risk. As we can see, the coefficients λ_0 are not statistically different from zero for the BVps portfolios. This is consistent with the Sharpe-Lintner hypothesis (SLH). The R^2 of the regression is only 0.7% for the case of CAPM while it goes up to 70% and 90% for the TFM and FF3FM respectively. The SMISI factor is priced and the market risk premium has the expected positive sign apart from the case of FF3FM though not significant at any level. The PL-model has relatively low R^2 while neither labor factor nor premium factor influence the returns. The results of the portfolios formed on beta coefficients are rather different. The R^2s increase and reach as high as 84.9% for the PL-model with the remaining models to follow closely. The intercepts of CAPM and TFM appear to be significant violating the SLH while the FF3FM has high R^2 value although none of its factors are priced. Panel B of Table 6 depicts the results for the period from July 2006 to August 2011. The TFM continues to have relatively high R^2 values while the FF3FM loses power relatively to its previously observed R^2 values. CAPM still performs poorly consistent with the results of JW. On the other hand the PL-model performs better in terms of R^2. The same tests[3] have been also carried out using the small sample. The findings differ significantly with regard to R^2 values which appear to be lower.

Table 6: Unconditional Cross-sectional regressions of CAPM, FF3FM, TFM and PL-model.

Panel A: 2001-2011 (BS)	λ_0	λ_1	λ_{SMISI}	λ_{NSI}	λ_{SMB}	λ_{HML}	λ_{labor}	λ_{prem}	R^2
BV per share	0.014	-0.004							0.007
	(0.75)	(-0.24)							
	-0.009		0.042	0.018					0.701
	(-0.75)		(3.74)*	(1.54)					
	0.009	-0.008			0.023	-0.002			0.914
	(0.78)	(-0.57)			(2.53)*	(-0.30)			
	0.009	0.004					-0.006	1.305	0.244
	(0.03)	(0.11)					(-0.99)	(0.93)	
Beta portfolios	0.003	0.005							0.825
	(2.98)*	(6.15)*							
	0.004		-0.002	0.005					0.828
	(2.10)**		(-0.34)	(3.11)*					
	0.002	0.008			-0.002	0.001			0.833
	(0.95)	(1.80)			(-0.36)	(0.48)			
	0.006	0.006					0.001	0.201	0.849
	(1.36)	(2.37)**					(0.91)	(0.85)	
Panel B: 2006-2011 (BS)	c_o	c_{mar}	c_{SMISI}	c_{NSI}	c_{SMB}	c_{HML}	c_{labor}	c_{prem}	R^2
BV per share	0.030	-0.019							0.456
	(3.52)*	(-2.59)*							

[3] The results are available from the authors upon request.

	0.014		0.022	-0.006					0.762
	(1.87)		(4.45)*	(-0.78)					
	0.003	0.003			0.003	-0.012			0.879
	(0.47)	(0.45)			(0.73)	(-2.83)*			
	0.028	-0.013					0.000	0.355	0.496
	(2.32)**	(-0.96)					(0.64)	(0.21)	
Beta portfolios	-0.001	0.018							0.006
	(-0.01)	(0.22)							
	-0.192		0.526	0.221					0.559
	(-2.13)**		(2.92)*	(2.47)*					
	-0.055	0.135			-0.069	-0.318			0.323
	(-0.17)	(0.33)			(-0.23)	(-1.05)			
	-0.209	0.363					0.144	-3.06	0.642
	(-1.19)	(3.01)*					(2.59)*	(-0.37)	

*,** depict significance at the 5% and the 10% level respectively.

In table 7 we present the unconditional cross-sectional regressions regarding the APT. Following Groenewold and Fraser (GF) (1997), in the first stage we estimate the factor sensitivities for each of the 20 portfolios (i.e. 10 portfolios sorted on betas and another 10 sorted on BV per share) for each of the 13 factors using OLS. In this stage, we retain only those factors that are priced at the 5% level. This way, we want to ensure that the number of independent variables is lower than the number of dependent variables. By following this procedure, GP, UNEM, CPI and LTGB variables of table 1 were excluded from the final step. It is worth mentioning here that the excess market return is also used in the model, since the initial results without market return have shown very low performance of the APT. The R^2 values never surpassed the 30% by including only macroeconomic variables. After eliminating insignificant factors one-by-one in reverse order of their *t*-ratios, as in GF , we are able to observe in table 7 the variation of significant factors in the tested portfolios. A noteworthy finding here is the high R^2 value of the model in the case of beta sorted portfolios reaching as high as 99%. However, the model leaves unexplained returns with the constant being significant at all usually levels.

Table 7: Unconditional Cross-sectional regressions of APT

Panel A: 2001-2011 (BS)	λ_0	λ_{MR}	λ_{DR}	λ_{EXR}	λ_{M3}	λ_{TB3M}	λ_{TS}	R^2
BV per share	-0.010	0.015			0.445			
	(-1.13)	(1.93)**			(5.95)*			0.835
Beta portfolios	0.006	0.004	-0.075	-0.006	-0.221	0.206	-0.039	
	(18.5)*	(15.3)*	(-10.6)*	(-5.51)*	(-14.9)*	(20.8)*	(-4.03)*	0.999

*,** depict significance at the 5% and the 10% level respectively.

The results of the conditional cross-sectional regressions are presented in table 8. The risk premia are demonstrated in the first column, the second column shows the *t*-ratio with the third and fourth columns to depict the normality test and the average GRS test coming from the time series first step regression respectively. We firstly note that in the case of BVps portfolios the variables of the TFM are priced though a proportion of portfolio returns left unexplained. The same happens with CAPM, while the market risk and the HML factor of the FF3FM appear to be significant with the constant not being statistically different from zero. Concerning PL-model no factor is priced. At this point we have to mention that the t statistics should be cared with caution. For example, there are cases where the distribution of the estimated risk premia are clearly not normal according to JB criterion, a result consistent with CT when macro-economic variables were used. As for the APT, we proceeded to model's estimation several times dropping those variables with insignificant risk premia in an attempt to identify a simplified version of the model. The evidence indicates that market return are still priced while two new factors, EXPIMP and IP not previously priced in the unconditional setting found to be significantly different from zero at the 10 per cent level (i.e. $|t|>1.30$). The positive signs of the coefficients for EXPIMP and IP seem to be correct, except that of the market index. Regarding the beta based portfolios almost no risk premia are priced apart from the case of the PL-model. In the APT if the market return is added as an additional risk factor, then the TS factor becomes significant. However, we chose to not include the market return in the table since it is not significant at any level even though the constant term diminishes in magnitude.

The GRS test depict that TFM clearly outperforms CAPM and FF3FM models in the first step time series regressions[4]. The test is not available in PL-model and in the APT. In the former case the regressions have been conducted separately for each one of the variables while in the latter case different number of factors have been found to be significant for each examined portfolio. However, averaging the estimated constant terms coming from the time series regressions across both kinds of portfolios we find significant differences between the APT and the TFM. In the case of beta sorted portfolios the average unexplained returns of the APT reach as high as 0.76% per month, significantly higher than the 0.16% per month of the TFM. Accordingly, in the case of BV per share portfolios the average unexplained returns are 0.65% and 0.31% for the APT and the TFM respectively.

[4] Messis and Zapranis (2014) provide analytical results of the TFM's superiority in explaining portfolio returns including momentum ones in the context of time series regressions.

Table 8: Estimated risk premia in conditional cross-section regression.

Panel A: 2001-2011 (BS)			λ_k	t	N	GRS test
BVps	CAPM	λ_0	-0.011	-2.06*	8.73	
		λ_{mar}	0.024	4.18*	5.83*	16.4
	TFM	λ_0	-0.018	-2.77*	35.8	
		λ_{SMISI}	0.019	2.56*	22.7	
		λ_{NSI}	0.032	3.97*	53.7	2.97*
	FF3FM	λ_0	-0.004	-0.53	739.4	
		λ_{mar}	0.017	1.61*	627.4	
		λ_{SMB}	0.007	1.13	35.1	
		λ_{HML}	-0.012	-2.07*	4.80*	10.36
	PLM	λ_0	0.004	1.03	651.2	
		λ_{mar}	-0.001	-0.11	67.4	
		λ_{prem}	0.000	-0.11	17.1	
		λ_{labor}	0.012	0.08	0.27*	N/A
	APT	λ_0	0.017	3.30*	0.97*	
		λ_{mar}	-0.007	-2.76*	4.34*	
		λ_{EXPIMP}	0.011	2.39*	1.37*	
		λ_{IP}	0.002	1.36*	167.1	N/A
Panel B: 2001-2011 (BS)			λ_k	t	N	GRS test
Beta port.	CAPM	λ_0	0.003	0.88	26.0	
		λ_{mar}	0.006	1.03	50.5	11.9
	TFM	λ_0	0.004	0.80	28.1	
		λ_{SMISI}	0.001	0.08	33.5	
		λ_{NSI}	0.005	0.62	47.8	1.39*
	FF3FM	λ_0	0.006	1.64*	16.6	
		λ_{mar}	0.002	0.47	20.9	
		λ_{SMB}	0.001	0.12	1733.1	
		λ_{HML}	-0.003	-0.60	68.9	5.52
	PLM	λ_0	-0.008	-1.46*	0.30*	
		λ_{mar}	0.025	3.49*	11.9	
		λ_{prem}	0.002	1.35*	90.7	
		λ_{labor}	0.041	0.27	466.2	N/A
	APT	λ_0	0.010	1.92*	48.7	
		λ_{TS}	0.062	0.64	67.3	N/A

* depicts significance at 10% level

3.3. Portfolio and models' performance in extreme market conditions

The results from our previous section indicate that portfolios formed with different criteria gain higher returns. Next, we examine if they are fundamentally riskier. According to Lakonishok et al. (1994) a portfolio would be fundamentally riskier if, first, underperforms the competitive one in some states of the world and second the underperformance would coincide with 'bad' states, in which the marginal utility of wealth is high, making the portfolio unattractive to risk-averse investors. In addition, Chan and Lakonishok (1993) state that downside risk is a major concern of money managers. Due to the fact that beta represents a stock's return sensitivity to market ups and downs, it is expected to be a good measure of downside risk. For this point of view, low beta portfolios should face lower downside risk than high beta portfolios. The opposite should happen when market rises.

Tables 9 and 10 present the results of the ten largest down and up-market months of both portfolios. We are able to distinguish between the two examined portfolios some very interesting characteristics. Firstly, in down markets, the lowest decile BVps portfolio appears to have lower returns with respect to the highest one. However, this fact could be explained in the case of beta based portfolios due to the lower beta coefficient, as presented previously in table 4. Instead, BVps portfolios do not exhibit such differences in the estimated betas that could explain those return divergences. Thus, there might be some other reason associated with this better performance.

In up markets, the lowest BVps portfolio does not differentiate from the highest one though this is the case between the two extreme beta based portfolios.

Table 9: Ten largest down market months: Simple Monthly Excess market Return (in Percent) and returns on portfolios formed using Book value per share and beta coefficients.

			Deciles									
	Month	Market	1	2	3	4	5	6	7	8	9	10
BV per share			**Low**									**High**
1	10/08	-17.0	-20.8	-18.4	-16.0	-18.0	-21.3	-15.6	-20.6	-23.1	-22.3	-25.7
2	9/02	-11.1	-5.5	-6.1	-6.9	-7.7	-8.8	-10.6	-8.7	-11.7	-10.1	-11.0
3	2/09	-11.0	-6.0	-5.6	-7.3	-13.0	-12.7	-10.6	-8.1	-12.4	-14.1	-20.2
4	9/08	-9.2	-8.8	-11.5	-10.5	-10.6	-10.1	-9.6	-11.4	-10.2	-11.0	-5.6
5	6/08	-8.8	-9.2	-6.9	-8.4	-6.1	-9.9	-9.6	-10.1	-8.8	-6.5	-8.7
6	1/09	-8.6	-5.1	-3.9	-2.9	-5.9	-8.0	-9.2	-8.8	-6.5	-8.7	-15.0
7	9/01	-8.4	-14.6	-10.3	-13.4	-12.9	-14.9	-11.8	-13.9	-12.5	-8	-9.2
8	5/10	-8.2	-8.0	-5.3	-6.3	-6.6	-7.8	-7.3	-7.8	-8.1	-7.8	-8.3
9	7/02	-8.0	-7.6	-6.0	-7.7	-9.2	-11.4	-8.3	-13.6	-10.4	-12.7	-9.9
10	11/08	-7.5	-11.5	-7.8	-11.7	-11.8	-9.7	-4.1	-7.0	-10.0	-8.7	-12.0
Average		-9.8	-9.7	-8.2	-9.1	-10.2	-11.5	-9.7	-11.0	-11.4	-11.2	-13.1
Beta based			**Low**									**High**
1	10/08	-17.0	-14.1	-13.4	-17.7	-16.6	-18.5	-19.1	-22.3	-25.0	-27.0	-25.8
2	9/02	-11.1	-5.8	-4.0	-6.3	-8.5	-8.6	-7.3	-8.4	-10.8	-10.3	-14.7
3	2/09	-11.0	-10.9	-11.8	-10.3	-9.3	-12.2	-13.7	-14.1	-8.9	-9.6	-10.8
4	9/08	-9.2	-6.7	-6.2	-6.0	-6.6	-9.2	-6.9	-8.1	-13.1	-15.6	-18.0
5	6/08	-8.8	-7.8	-7.8	-9.1	-6.9	-11.3	-7.7	-10.3	-8.5	-11.4	-10.3
6	1/09	-8.6	-2.8	-4.6	-4.1	-9.6	-9.4	-9.0	-13.5	-10.0	-6.0	-4.1
7	9/01	-8.4	-5.0	-8.6	-7.7	-9.7	-8.2	-10.5	-8.1	-14.4	-17.8	-25.8
8	5/10	-8.2	-5.0	-5.4	-6.8	-6.9	-6.9	-7.4	-9.0	-9.4	-6.9	-9.9
9	7/02	-8.0	-6.8	-11.2	-6.3	-5.6	-10.2	-9.5	-11.1	-14.3	-8.7	-12.8
10	11/08	-7.5	-4.0	-5.1	-6.6	-4.8	-7.8	-12.9	-11.2	-12.2	-10.6	-17.0
Average		-9.8	-6.9	-7.8	-8.1	-8.4	-10.2	-10.4	-11.6	-12.7	-12.4	-14.9

Table 10: Ten largest up market months: Simple Monthly Excess market Return (in Percent) and returns on portfolios formed using Book value per share and beta coefficients.

			Deciles									
	Month	Market	1	2	3	4	5	6	7	8	9	10
BV per share			**Low**									**High**
1	4/09	9.4	19.4	14.5	15.4	18.4	18.9	15.5	17.1	20.3	18.1	23.3
2	9/10	8.7	11.7	13.3	10.2	10.7	11.9	9.4	9.3	9.6	9.6	7.9
3	3/09	8.5	11.0	11.3	9.3	9.2	11.7	7.0	9.6	9.4	9.9	14.7
4	10/02	8.5	11.6	7.8	3.6	9.0	6.4	5.7	3.3	4.7	2.3	4.3
5	4/03	8.0	8.8	5.8	9.5	8.5	8.4	9.1	9.7	7.8	7.3	10.9
6	7/09	7.4	8.7	10.6	9.1	10.2	11.2	9.2	9.2	10.0	9.7	8.4
7	11/01	7.4	11.3	11.0	8.3	9.3	9.2	6.7	8.6	7.0	4.6	8.0
8	7/10	6.9	7.5	6.4	8.1	6.6	8.6	6.3	8.0	5.9	8.5	7.7
9	12/10	6.5	6.0	7.0	7.3	6.1	6.9	6.1	6.6	9.3	7.5	8.6
10	3/10	5.9	7.7	7.3	6.7	7.3	7.0	7.7	6.7	6.5	6.6	7.2
Average		7.7	10.4	9.5	8.7	9.5	10.0	8.3	8.8	9.1	8.4	10.1
Beta based			**Low**									**High**
1	4/09	9.4	3.2	8.6	10.4	14.2	17.1	21.4	26.9	23.0	18.9	31.9
2	9/10	8.7	6.0	6.6	8.1	8.8	10.9	10.9	12.2	12.9	13.3	13.3
3	3/09	8.5	2.7	6.4	7.2	10.2	10.0	9.0	11.0	10.7	17.0	17.9
4	10/02	8.5	-0.8	-0.2	1.1	4.1	7.5	5.9	4.1	6.5	9.8	20.1
5	4/03	8.0	4.4	5.3	7.0	7.0	5.8	5.1	8.1	12.6	10.5	16.4
6	7/09	7.4	5.5	6.1	7.8	7.6	7.9	8.1	9.1	8.7	17.6	19.2
7	11/01	7.4	0.9	5.0	3.3	7.8	8.6	7.8	6.8	8.8	12.1	19.6
8	7/10	6.9	2.9	4.7	5.5	5.3	6.0	7.2	9.7	12.1	8.9	10.7
9	12/10	6.5	4.6	4.6	5.9	7.0	6.2	7.8	7.4	7.5	7.4	15.0
10	3/10	5.9	3.6	3.3	4.7	6.4	6.6	6.9	8.0	7.2	10.7	13.0
Average		7.7	3.3	5.0	6.1	7.8	8.7	9.0	10.3	11.0	12.6	17.7

Following Chan and Lakonishok (1993), we also conduct cross-sectional regression exploring the models' performance during extreme market conditions. This time, a large down (up) market is defined as a month where the market excess return is larger in magnitude than the median of those observations that are negative (positive). The median of negative markets was found to be -2.43% from 26 observations while the median of positive markets was 2.22% including 34 observations. The panel data method is employed in this case primarily due to the low number of observations that could be possibly distort the results, which are displayed in tables 11 and 12.

Our results indicate that all models leave unexplained returns in down markets while the R^2 values are similar. However, the models perform better in up markets. In the APT, we chose to include the market factor in the case of beta sorted portfolios both in up and down markets since the findings without this particular factor were poor. Furthermore, the CAPM seems to work reasonable well at both up and down markets compared to the findings reported earlier in terms of R^2 values. As for the SMISI factor of the TFM, it shows the expected negative (in the case of beta sorted portfolios) and positive sign in down and up markets respectively.

Table 11: Cross-sectional regression results classified by down market months

Panel A:CAPM,TFM, FF	λ_0	λ_{mar}	λ_{SMISI}	λ_{NSI}	λ_{SMB}	λ_{HML}	λ_{labor}	λ_{prem}	R^2
BV per share	-0.067	0.004							0.829
	(-6.75)*	(0.46)							
	-0.070		0.013	0.008					0.831
	(-6.26)*		(1.41)	(0.69)					
	-0.033	-0.029			0.011	-0.019			0.840
	(-3.16)*	(-2.50)*			(1.94**	(1.95)**			
	-0.067	0.005					-0.062	0.001	0.829
	(-6.92)*	(0.54)					(-0.40)	(1.08)	
Beta portfolios	-0.010	-0.051							0.794
	(-7.09)*	(-57.4)*							
	-0.013		-0.036	-0.051					0.796
	(-5.19)*		(-2.00)*	(-24.1)*					
	-0.019	-0.041			-0.027	0.002			0.792
	(-4.27)*	(-9.12)*			(-2.84)*	(0.31)			
	-0.005	-0.055					0.182	-0.001	0.799
	(-2.21)*	(-20.1)*					(2.65)*	(-1.09)	
Panel B: APT	λ_0	λ_{mar}	λ_{EXPIMP}	λ_{IP}	λ_{TS}				R^2
BV per share	-0.055	-0.008	-0.036	-0.004					
	(-4.69)*	(-0.74)	(-2.22)*	(-0.94)					0.835
Beta portfolios	-0.004	-0.056			0.141				
	(-1.92)**	(-28.2)*			(1.03)				0.821

*,** depict significance at 5% and 10% respectively.

Table 12: Cross-sectional regression results classified by up market months

Panel B: Best months	λ_o	λ_{mar}	λ_{SMISI}	λ_{NSI}	λ_{SMB}	λ_{HML}	λ_{labor}	λ_{prem}	R^2
BV per share	0.013	0.049							0.820
	(1.10)	(4.08)*							
	0.006		0.001	0.058					0.817
	(0.69)		(0.11)	(5.46)*					
	-0.000	0.061			0.015	0.007			0.821
	(-0.01)	(4.42)*			(2.32)*	(1.12)			
	0.013	0.049					0.075	-0.000	0.821
	(1.28)	(5.34)*					(0.69)	(-0.16)	
Beta portfolios	0.008	0.052							0.646
	(6.63)*	(53.6)*							
	0.005		0.053	0.058					0.666
	(-2.01)*		(1.89)**	(20.3)*					
	0.031	0.034			0.035	-0.041			0.667
	(2.95)*	(3.89)*			(4.54)*	(-2.11)*			
	-0.005	0.061					-0.618	0.001	0.675
	(-1.03)	(11.9)*					(-8.25)*	(1.06)	
Panel A2: APT	λ_0	λ_{mar}	λ_{EXPIMP}	λ_{IP}	λ_{TS}				R^2
BV per share	0.011	0.049	-0.010	-0.001					
	(1.12)	(4.92)*	(-1.49)	(-0.17)					0.821
Beta portfolios	0.001	0.058			-0.478				
	(0.01)	(15.7)*			(-3.41)*				0.661

*,** depict significance at 5% and 10% respectively.

4. Conclusions

This paper examines the efficacy of different models to explain the relationship between expected returns and risk in the cross-sectional context. We introduce a novel approach which is primarily based on the time varying nature of betas. The new TFM incorporates two variables. The first one is the 'SMISI' and captures the risk associated with the difference between 'Superior' and 'Ineferior' stocks whose betas are increasing and decreasing in market return respectively. The second variable, the 'NSI', is constituted from invariant betas and operates as the market factor. The proposed model was compared against three models previously presented in the literature. Our results show that the proposed model outperforms alternative models.

The study shows that in the cross-sectional analysis both conditionally and unconditionally, the stock market prices different risk factors. Related to the BVps portfolios, the SMISI factor is priced and the market risk premium has the expected positive sign apart from the case of FF3FM though not significant at any level. As for the PL-model, it has relatively low R^2 while neither labor nor premium factors influence the returns. The results of the portfolios formed on beta coefficients depict that PL-model increases its R^2 with the rest models to follow closely. In the case of APT, different risk factors are priced within the two kinds of portfolios. An interesting finding is the model's high R^2 value regarding the beta sorted portfolios even though the constant is statistically different from zero.

The conditional cross-sectional regressions in the case of BVps portfolios identify the power of the TFM variables in explaining asset returns even though a proportion of them left unexplained. Unexplained returns are also evidenced in the case of the CAPM. The market and the HML factors in the FF3FM appear to be significant with the constant not being statistically different from zero. Regarding the PL-model no factor is priced. In the APT model, two new factors appear to be significant (i.e. EXPIMP and IP) other than the market risk not previously mentioned in the unconditional setting. For the beta sorted portfolios, almost no risk premia were found to be statistically different from zero in the case of the PL-model. Moreover, the GRS test calculated in the first step time series regressions depict the outperformance of TFM in relation to CAPM and FF3FM models.

In extreme market conditions, the selected portfolios appear to have a different reaction. A downward movement of the markets has a lower impact on the lower portfolios than in the higher ones. However, in an upward movement of the markets the lowest BVps portfolio does not differentiate from the highest one though this is the case between the two extreme beta sorted portfolios. The models' performance in extreme conditions show that all models in down months leave unexplained returns but they perform better in up months.

The implications of this study show that there are additional factors other than the market risk that affect stock returns. The new risk factors which found to be significant both in time series and cross section analyses, give valuable information of better understanding the characteristics of returns, targeting the reinforcement of stock market efficiency.

References

Andersen, T., Bollerslev, T., Diebold, F., Wu, J. 2006. Realized beta: Persistence and predictability. *Advances in Econometrics* 20: 1-39.

Banz, R. 1981. The relation between return and market value of common stocks. *Journal of Financial Economics* 9: 3-18.

Banz, R., Breen, W. 1986. Sample-dependent results using accounting and market data: Some evidence. *Journal of Finance* 41: 779-793.

Beenstock, M., Chan, K. 1988. Economic forces in the London stock market. *Oxford Bulletin of Economics and Statistics* 50: 27-39.

Berk, J. 1995. A critique of size related anomalies. *Review of Financial Studies* 8: 275-286.

Bhardwaj, R., Brooks, L. 1993. Dual betas from bull and bear markets: Reversal of the size effect. *Journal of Financial Research* 16: 269-283.

Bodie,Z., Kane, A., Marcus, A. 2002. Investments. 5th ed. Mc Graw-Hill Companies.

Chan, L., Lakonishok, J. 1993. Are the reports of beta's death premature? *Journal of Portfolio Management* 19: 51-62.

Chan, L., Hamao, Y., Lakonishok, J. 1991. Fundamentals and stock returns in Japan. *Journal of Finance* 46: 1467-1484.

Chen, N. 1983. Some empirical tests of the Theory of Arbitrage Pricing. *Journal of Finance* 38: 1393-1414.

Chen, N., Roll, R., Ross, S. 1986. Economic forces and the stock market. *Journal of Business* 59: 383-403.

Clare, A., Thomas, S. 1994. Macroeconomic factors, the APT and the UK stock market. *Journal of Business Finance and Accounting* 21: 309-330.

Clinebell J., Squires, J., Stevens, J. 1993. Investment performance over bull and bear markets: Fabozzi and Francis Revisited. *Quarterly Journal of Business and Economics* 32: 14-25.

Cuthbertson, K., Nitzsche, D. 2004. Quantitative financial economics. 2nd ed. John Wiley & Sons.

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

Daves, P., Ehrhardt, M., Kunkel, R. 2000. Estimating systematic risk: The choice of return interval and estimation period. *Journal of Financial and Strategic Decisions* 13: 7-13.

Davis, J. 1994. The cross-section of realized stock returns: The pre-COMPUSTAT evidence. *Journal of Finance* 49: 1579-1593.

Fabozzi, F., Francis, F. 1977. Stability tests for alphas and betas over bull and bear market conditions. *Journal of Finance* 32: 1093-199.

Faff, R., Brooks, R. 1998. Time-varying beta risk for Australian industry portfolios: an exploratory analysis. *Journal of Business Finance and Accounting* 25: 721-745.

Fama, E., French, K. 1992. The cross-section of expected stock returns. *Journal of Finance* 47: 427-465.

Fama, E., French, K. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51: 55-84.

Fama, E., French, K. 2004. The Capital Asset Pricing Model: Theory and evidence. *Journal of Economic Perspectives* 18: 25-46.

Fama, R., MacBeth, J. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81: 607-636.

Fletcher, J. 2000. On the conditional relationship between beta and return in international stock returns. *International Review of Financial Analysis* 9: 235-245.

Fraser, P., Hamelink, F., Hoesli, M., MacGregor, B. 2004. Time-varying betas and the cross-sectional return-risk relation: evidence from the UK. *The European Journal of Finance* 10: 255-276.

Gibbons, R., Ross, S., Shanken, J. 1989. A test of the efficiency of a given portfolio. *Econometrica* 57: 1121-1152.

Gregory, A., Harris, R., Michou, M. 2001. An analysis of contrarian investment strategies in the UK. *Journal of Business Finance and Accounting* 28: 1193-1228.

Groenewold, N., Fraser, P. 1997. Share prices and macroeconomic factors. *Journal of Business Finance and Accounting* 24: 1367-1383.

Isakov, D. 1999. Is beta still alive? Conclusive evidence from the Swiss stock market. *The European Journal of Finance* 5: 202-212.

Jacoby, G., Fowler, D., Gottesman, A. 2000. The Capital Asset Pricing Model and the liquidity effect: A theoretical approach. *Journal of Financial Markets* 3: 69-81.

Jagannathan, R., Wang, Z. 1996. The conditional CAPM and the cross-section of expected returns. *Journal of Finance* 51: 3-53.

Jegadeesh, N. 1992. Does market risk really explain the size effect? *Journal of Financial and Quantitative Analysis* 27: 337-351.

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

Lehmann, B., Modest, D. 1988. The empirical foundations of the Arbitrage Pricing Theory. *Journal of Financial Economics* 21: 213-254.

Levis, M., Liodakis, M. 2001. Contrarian strategies and investor expectations: The U.K. evidence. *Financial Analysts Journal* 57: 43-56.

Levy, R. 1974. Beta coefficients as predictors of returns. *Financial Analysts Journal* 30: 61-69.

Lin, W., Chen, Y., Boot, J. 1992. The dynamic and stochastic instability of betas: Implications for forecasting stock returns. *Journal of Forecasting* 11: 517-541.

Lintner, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budget. *Review of Economics and Statistics* 47: 13-37.

Messis, P., Zapranis, A. 2014. Asset pricing with time-varying betas for stocks traded on S&P 500. *Applied Economics*, DOI: 10.1080/00036846.2014.964833.

Parhizgari, A., Dandapani, K., Prakash, A. 1993. Arbitrage pricing theory and the investment horizon. *Journal of Business Finance and Accounting* 20: 27-40.

Perold, A. 2004. The Capital Asset Pricing Model. *Journal of Economic Perspectives* 18: 3-24.

Pettengill, G., Sundaram, N., Mathur, I. 1995. The conditional relation between beta and returns. *Journal of Financial and Quantitative Analysis* 30: 101-116.

Roll, R. 1977. A critique of the asset pricing theory's tests: Part I: on past and potential testability of the theory. *Journal of Financial Economics* 4: 129-176.

Ross, S. 1976. The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory* 13: 341-360.

Sharpe, W. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance* 19: 425-442.

Stock, J., Watson, M. 1989. New indexes of coincident and leading economic indicators. In Olivier Jean Blanchard and Stanley Fischer , editors. NBER Macroeconomics Annual 1989.

Tang, G., Shum, W. 2003. The conditional relationship between beta and returns: Recent evidence from international stock markets. *International Business Review* 12: 109-126.

Wiggins, J. 1992. Betas in up and down markets. *Financial Review* 27: 107-123.

Woodward, G., Anderson, H. 2009. Does beta react to market conditions? Estimates of 'bull' and 'bear' betas using a nonlinear market model with an endogenous threshold parameter. *Quantitative Finance* 9: 913-924.

Zarowin, P. 1990. Size, seasonality, and stock market overreaction. *Journal of Finance and Quantitative Analysis* 25: 113-125.