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The Prediction Performance of Asset Pricing Models and Their Capability of Capturing the Effects of Economic Crises: The Case of Istanbul Stock Exchange

Varlık Fiyatlandırma Modellerinin Tahmin Performansı ve Ekonomik Krizlerin Etkilerini Yansıtma Güçleri: İstanbul Menkul Kıymetler Borsası Örneği

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Abstract

This paper is prepared to test the common opinion that the multifactor asset pricing models produce superior predictions as compared to the single factor models and to evaluate the performance of Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM). For this purpose, the monthly return data from January 1996 and December 2004 of the stocks of 45 firms listed at Istanbul Stock Exchange were used. Our factor analysis results show that 68,3 % of the return variation can be explained by five factors. Although the APT model has generated a low coefficient of determination, 28,3 %, it proves to be more competent in explaining stock return changes when compared to CAPM which has an inferior explanation power, 5,4 %. Furthermore, we have observed that APT is more robust also in capturing the effects of any economic crisis on return variations.

Keywords: Arbitrage pricing theory, capital asset pricing model, economic crisis, factor analysis, discriminant analysis

Özet

Bu çalışma, çok faktörlü varlık fiyatlandırma modellerinin tek faktörlü modellere kıyasla daha üstün tahminler ürettikleri yönündeki yaygın görüşü test etmek ve Arbitraj Fiyatlama Teorisi (APT) ile Finansal Varlıkları Fiyatlandırma Modeli (CAPM)'nin tahmin performanslarını karşılaştırmak amacıyla hazırlanmıştır. Bu amaçla, İstanbul Menkul Kıymetler Borsası'nda hisse senetleri işlem gören 45 firmaya ait Ocak 1996 – Aralık 2004 dönemini kapsayan aylık getiri bilgileri kullanılmıştır. Faktör Analizi sonuçları getiri değişkenliğinin 68,3 %'ünün beş faktör yardımıyla açıklanabildiğini göstermiştir. APT modelinin 28,3 % gibi düşük bir belirlilik katsayısı ortaya koymasına rağmen, 5,4 % gibi daha düşük bir katsayı üreten CAPM ile karşılaştırıldığında daha *başarılı olduğu anlaşılmıştır. Ayrıca, APT'nin, ekonomik krizlerin getiri dağılımları üzerindeki etkilerini belirlemede de daha sağlam bir model olduğu görülmüştür.*

Anahtar Kelimeler: *Arbitraj fiyatlama teorisi, finansal varlıkları fiyatlandırma modeli, ekonomik kriz, faktör analizi, diskriminant (ayrım) analizi*

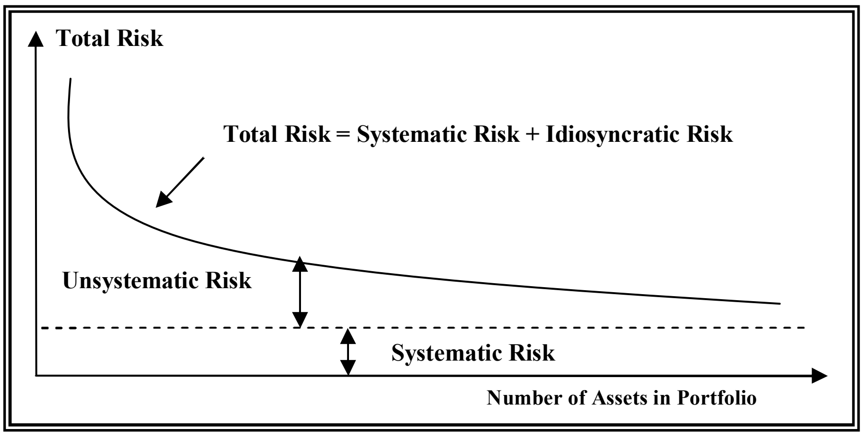
1. Introduction and Theoretical Framework

In the literature of finance, risk is simply defined as the variation of returns. The total risk associated with a financial asset investment, especially investments in stocks, has two basic components; systematic and unsystematic risks. Although the systematic risk factors are closely related with the whole economy and affect all of the financial assets traded, the unsystematic risk factors are mainly specific and unique to each asset.

A rational investor is the one who wants to earn much enough at a given risk level undertaken. In other words, a higher level of risk incurred must be awarded with a higher rate of return. On the other hand, it cannot be expected for every investor to have an identical risk attitude so that while some investors are risk avoiders who are willing to get enough return for a reasonably low risk level, some others like bearing high levels of risk with the expectation of receiving much more return as possible. Whatever risk profile an investor has, it should be noted that the main point is to receive satisfactorily high returns at rationally reduced risk levels. Reducing risks associated with a financial investment is the basic concern of portfolio construction and management.

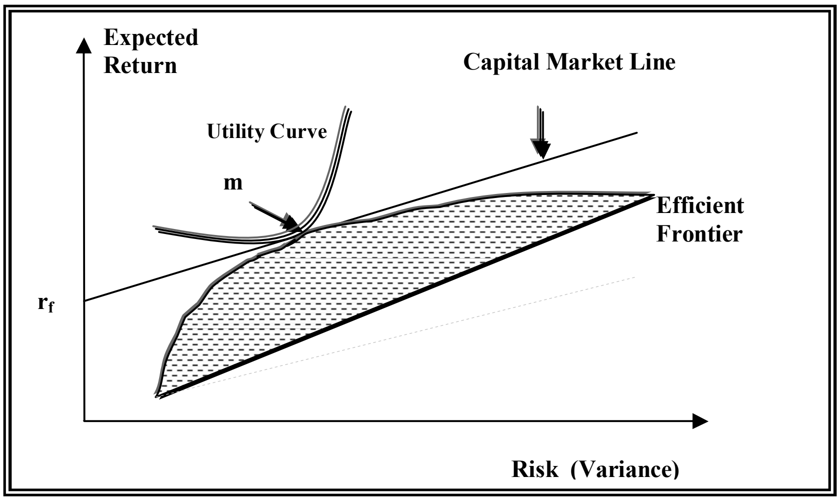
Markowitz (1952: 77-91) suggests that a well diversified portfolio is exposed only to systematic risk since unsystematic, or idiosyncratic risks are theoretically eliminated through constructing sufficiently diversified portfolios (Figure 1). Therefore, the focus is only on both dealing with the management of systematic risk of any investment and deciding the right time for trading. The addition of financial assets from different countries helps increase portfolio return without increasing the total risk. (Ceylan and Korkmaz, 2008: 713)

Figure 1: **Systematic and Unsystematic Risks**



Portfolio diversification is based on the common judgment that the total risk of any portfolio can be reduced to an acceptable level without allowing for any deviance from the expected return through adding financial assets with no perfect positive correlations between each other to the portfolio. Investors make their choices from among investment alternatives in order to get a higher return at the same risk level or to bear lower risk for a given return. The set of alternative portfolios generating the highest returns at the same level of risk is called the Set of Efficient Portfolios and the risk-return curve that is determined by these portfolios is named the Efficient Frontier (Figure 2).

Figure 2: **Capital Market Line, Efficient Frontier, and Utility Curves**



In the above figure, utility curves reflect the risk behaviors of investors while the capital market line represents the theoretical relationship between given risk levels and corresponding expected returns. The risk free return is symbolized with the term $\mathbf{r_f}$. The tangent point (m) of the capital market line, utility curve, and efficient frontier refers to the expected return of the best investment alternative convenient to investor's given risk behavior.

Despite its simplicity and ease to comprehend, if more assets are added to the portfolio, Markowitz's model becomes more complicated in terms of risk and return calculations. Along with the increasing number of assets in a portfolio, the expected return and return variance of the portfolio are computed using the following formulas (Konuralp, 2001: 261):

$$\text{Expected Return of a Portfolio} = E(R_P) = \sum w_i . E(R_i) \qquad \textbf{(1)}$$

$$\text{Variance} = \sigma_p^{\ 2} = \sum_{i=1} \sum_{j=1} w_i . w_j . \rho_{ij} . \sigma_i . \sigma_j \qquad \textbf{(2)}$$

where,

$w_{i,j}$: Weights of *i*th and *j*th assets in portfolio

$\rho_{i,j}$: Correlation between the returns of assets *i* and *j*

$\sigma_{i,j}$: Return variance of assets *i* and *j*

$E(R_i)$: Expected return of *i*th asset

The challenging computational complexity in Markowitz's model has encouraged researchers to search for more functional and user friendly models to predict and compute expected return. As a result of the consequent trend in modeling expected return depending on specific risk factors, a significant number of model proposals based on single and/or multifactor structures were presented.

1.1. Single Factor Models and Capital Asset Pricing Model (CAPM)

Modeling studies concerning only one systematic factor as a major determinant on expected returns are called single factor models. These models assume that the systematic risk component of a financial investment can be covered by using a single proper factor as the predictor of expected return. The risk factor taken as predictor variable in models has been either a macroeconomic indicator or a specific index such as consumption index. The risk return relationship is examined in the form of a simple regression equation as presented in Equation 3:

$$E(R) = \alpha + \beta X_F \qquad \textbf{(3)}$$

In the above equation, E (R) is used for the expected rate of return and X_F denotes the systematic risk factor. α simply represents the constant value that is free of the effect of the risk factor concerned in the model and β is the regression coefficient. Sharpe and Lintner (1972: 453-458) proposed a model based on a simple regression equation in which the market index return took place as the predictor.

The most important attempt that is considered to be a milestone in the related literature to calculate expected returns on financial assets as based on a single risk factor was the Capital Asset Pricing Model (CAPM) developed by William F.Sharpe (1964: 425-442). The model that can be regarded as a developed version of Markowitz's approach suggests that the only systematic risk affecting expected return is the market risk and brought two important concepts to the literature: *market portfolio* and *risk free rate of return*. According to the CAPM, the expected rate of return on any financial asset can be calculated using the following formula:

$$E(R_i) = R_f + \beta \left\lfloor E(R_m) - R_f \right\rfloor \qquad \textbf{(4)}$$

In Equation 3, E (R_i) represents the expected return of financial asset *i* while R_f refers to the rate of return on a risk free asset such as treasury bills, government bonds an so on. E (R_m) is the symbol used for the expected rate of return on the market portfolio and β is referred to as the sensitivity of the returns on financial asset *i* to the changes in returns of the market portfolio. The multiplication of β coefficient with the term inside the parenthesis gives the risk premium assigned to that financial asset. β coefficient unique to a financial asset is computed using the Equation 5:

$$\beta = \frac{Cov(i,m)}{\sigma_m^{\ 2}} \quad \textbf{(5)}$$

where;

Cov(i,m) : Covariance of asset *i* and market portfolio returns

σ_m^2 : Variance of market return

CAPM says that the theoretical equilibrium presented in the above equations is expected to be valid for both well diversified portfolios and single financial assets as long as the efficient market conditions are met for any capital market. These conditions as the first and most important assumptions of CAPM are so restrictive and in most cases become unrealistic.

The strength of efficiency in a market is measured according to the extent to which all the information relevant to investment is fully obtained and immediately reflected to asset prices by investors. Fama (1970: 383-417) states that a strongly efficient market is a place where:

- The main goal of investors is to maximize their wealth for a certain period of time,
- Investment decisions are made according to their risk and return expectations,
- Every investors has the same or identical risk and return projections,
- Financial assets are traded for the same particular periods,
- All the relevant information is accessed immediately on a free basis with no cost.

Beside the assumption of efficient market, CAPM has three additional assumptions essential to its applicability and reliability (Bodie ve Marcus, 1999: 224):

a) There is a risk free asset and all the investors has the chance to borrow and invest in infinite amounts,
b) Tax charges on transactions and transaction costs incurred are very low or don't exist,
c) The number of financial assets traded in the market is constant and all the assets can be divided to and traded in little amounts as possible.

The right assessment and prediction of key variables in the CAPM is crucial to the success of the models. Beta coefficients and risk free rate of return must be truly and precisely examined and a proper definition of market portfolio should be made so that there is no suspicion about whether or not the cited market return is reliable enough.

In the finance literature, it is possible to see some model designs similar to CAPM. As the first example, the Consumption-Based CAPM (CCAPM) is another version of CAPM in which the consumption index changes are taken as a proxy for systematic risk factor premiums. The second example is the Zero-Beta CAPM which suggests that the risk free rate of return should be determined as the average return of a portfolio or a financial asset with no sensitivity to the market portfolio.

Even though CAPM is a model proposal easily understood and applied, its restrictive and iunrealistic assumptions make the model frequently criticized in terms of reliability and validity. Especially, due to the absence of strongly efficient markets throughout the world, the theory is considered not to be able to go beyond being a utopia.

To eliminate the pitfalls that stem from these restrictive and rigid assumptions and to create a more realistic model, the researchers focused on the construction of new asset pricing theories assuming more down-to-earth circumstances and put all their efforts in designing theories and models including several factors that they considered to be appropriate determinants on systematic risk premiums of financial assets.

1.2. Multifactor Models and Arbitrage Pricing Theory (APT)

All the multifactor asset pricing models try to explore the risk contribution of systematic factors effective on expected returns by constructing linear multiple regression equations that are expected to best represent the relationship between risk factors and asset returns.

The most important one of the multifactor prediction models is the Arbitrage Pricing Theory which was developed by Stephen A. Ross (1976: 341-360). This theory has been considered an alternative to the Capital Asset Pricing Model and does not presume the presence of a fully efficient market. But, there are a few assumptions mentioned below on which the theory is based:

a) The capital market fits the conditions of perfect competition,
b) Investors are rational under certainty conditions, which means that they prefer more wealth to he less,
c) The stochastic process explaining how asset returns exist can be explained by a linear K-factor model,
d) Market does not allow for arbitrage opportunities arising from the violation of the law of one price. If any arbitrage opportunity existed, investors would immediately react in order to benefit from that situation by buying the asset in the market where it has been undervalued and then selling where the asset has been relatively overvalued. All these attempts would make the existing arbitrage opportunity suddenly disappear.

Ross starts his model explanation with a single factor model resembling the CAPM and formulates the risk-return relationship using the following single equation (Bolak, 2001: 270):

$$r_i = \alpha_i + \beta_i F + e_i \qquad \textbf{(6)}$$

In the equation, the actual rate of return is abbreviated by r_i, α_i refers to the expected rate of return on the asset *i*, F denotes systematic risk factor, and β_i represents the sensitivity of the asset's returns to the risk factor. The prediction error arising from the effect of idiosyncratic factors is symbolized with e_i.

The theory assumes that all the firm-specific risk factors (e_i) can be fully eliminated if a portfolio has been sufficiently diversified and therefore systematic risk component becomes the only case for portfolios. The return estimation equation turns out to be in a new form presented below.

$$r_p = E(R_p) + \beta_p F \quad \textbf{(7)}$$

It is a simplifying assumption to say that there is only one systematic risk factor affecting asset returns. To get closer to the reality, the theory suggests the use of multiple variables as determinants on systematic risk in order to cover all the effects of potential systematic risk factors. In most of the relevant studies performed, major macroeconomic indicators such as interest rate, inflation, gross domestic product (GDP), have been preferred as the representatives of potential systematic risk factors.

A typical multifactor APT Model is similar to linear multiple regression models. Expected return on any financial asset is finally formulated as in the Equation 8:

$$E(R_p) = r_f + \sum \beta_{p,i}.(E(R_{Fi}) - r_f) \quad \textbf{(8)}$$

In the above equation, E (R_P) is the expected rate of return on portfolio, E (R_{Fi}) is referred to as the expected rate of return on *i*th factor portfolio, $\beta_{p,i}$ constitutes the sensitivity of portfolio's return to the factor portfolio *i*, and r_f represents risk free rate of return. The difference term in parenthesis is called the risk premium of the factor portfolio.

A factor portfolio is a portfolio whose return distribution has no correlation (zero correlation) with those of other factor portfolios. This situation is seen as a bottleneck for the implementation of the theory because examining separate factor portfolios not correlated to each other is so difficult a business to succeed. The exploration of not correlated factor portfolios is a task similar to searching for explanatory variables fulfilling the statistical requirement of absence of linear multicollinearity (Maddala, 2004: 278).

Factor analysis is generally used to construct an appropriate regression model so as to predict expected return with uncorrelated factor variables. The basic steps in constructing a multifactor asset pricing model are summarized as follows:

- Selection of financial assets to compute risk factor scores and examination of the actual rates of return of these assets on a certain time basis (daily, monthly, or yearly)
- Calculation of factor coefficients and scores,
- Determination of factor loads and risk premiums,
- Testing the reliability of risk premiums through periodical segmentation,
- Regress actual returns on factor loads.

At the step of computing factor loads and risk premiums, a separate equation used to determine factor loads to be taken as risk premiums is constructed for each financial asset (Equation 9):

$$R_{it} = b_{i0} + b_{i1}\delta_1 + b_{i2}\delta_2 + \ldots\ldots.. + b_{in}\delta_n + u_{it} \qquad \textbf{(9)}$$

where,

R_{it} : Rate of return on the financial asset *i* at time *t*

$b_{i,j}$: Sensitivity of the asset *i* to the factor *j*

δ_j : The factor score *j*

$u_{i,j}$: Unexplained portion of actual return

By regressing the mean rate of returns on the factor loads ($b_{i,j}$) determined, a final regression equation is obtained that can be used in predicting expected returns (Equation 10).

$$E(R_i) = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \ldots\ldots. + \lambda_n b_{in} \qquad \textbf{(10)}$$

where;

$E(R_i)$: Expected rate of return on the asset *i*

λ_0 : Risk free rate of return

λj : Risk premium related to the factor *j*

b_{ij}: Coefficient showing the sensitivity of the asset *i* to the factor j

The theory assumes the validity of the suggestion the APT points out also for individual assets if it is really valid for well diversified portfolios.

The second remarkable theory in the relevant literature employing multifactor modeling procedure is the Three-Factor Model proposed by Fama and French (1993: 3-56). The Three-Factor Model is another replication of the multifactor APT models. As different from the APT models, three predetermined systematic risk factor are considered; market risk premium (the return of market portfolio in excess of risk free return), the difference between the mean rates of return of small and big-scaled companies, and the difference between the average return of the companies with high book to market ratios and the average return of those with low book to market ratios (Hu, 2007: 113).

The presence of two main theories, APT and CAPM, in the field of asset pricing has cast strong concern in investigating the superiority of these models to each other. Following the introduction of these theories to the literature, a huge number empirical studies were carried out aiming to compare their performance. Most of the findings reported in these studies have provided results favoring the APT models against the CAPM even in the emerging markets. There are few studies that suggest the superiority of CAPM over APT.

Dhankar and Singh (2005: 14) showed that the multifactor APT models could provide better results than the CAPM in the Indian Stock Market on monthly and weekly returns data. In another research carried out by Sun and Zhang (2001: 617)in

America using the data of eight forestry-related companies' financial performance, some empirical results were reported favoring the better performance of the APT models as compared to CAPM. As a unique study arguing the applicability of the APT models, Altay (2005: 217 – 237) pointed out that unexpected interest rate and inflation changes proved to be statistically significant determinants on stock returns in Germany. However, he also stated that the same judgment couldn't be made for the stock market in Turkey.

This paper is prepared to compare the prediction performance of the APT and CAPM models in Turkey and to explore whether or not these two theories can reflect the effects of economic crisis into estimations and presents some empirical evidence favoring the use of the APT models instead of the CAPM.

2. Empirical Research

The research reported in this paper mainly aims both to argue the capability of the multifactor APT and CAPM in catching the effects on economic crisis when estimating asset returns in Turkey and to compare the performance of these two models to each other. By applying factor analysis, we intend to investigate what macroeconomic indicators can be regarded as the sources of systematic risk. To determine the possible sources of systematic risk, 18 macroeconomic indicators and ISE (Istanbul Stock Exchange) 100 index have been considered.

2.1. Sample Selection and Data Collection

Since the required data are not accessible for all the companies listed in the ISE 100 index, only a sample of 45 companies with full data- 20 of them are listed also in the ISE 30 Index - has been selected from among 100 companies. The TL-based, monthly actual rates of return data relating the stocks of the companies in the sample for the period from January 1996 to December 2004 (108 observations for each stock) were downloaded from the official website of the Istanbul Stock Exchange and the data on the predetermined macroeconomic indicators for the same time interval were collected from the official website of the Central Bank of Turkey. Table 1 includes a full list of the macroeconomic variables considered in our analysis.

It forced us to make some adjustments on the data that many of the macroeconomic indicators are index values computed based on a constant year. We had to convert such index values to chain index values in order to be able to see the monthly changes in the indices. Besides that challenge, for some variables take big values that are not comparable to others, we applied logarithmic transformation on these variables.

Table 1: List of the Macroeconomic Variables

CODE	VARIABLE EXPLANATION
M1	ISE 100 INDEX RETURN (Monthly)
M2	LOG(CHANGE IN IMPORT)
M3	LOG(CHANGE IN EXPORT)
M4	CONSUMER PRICE CHAIN INDEX (TUFE)
M5	Monthly Change in Interest Rate for Saving Deposits
M6	% Change in Domestic Borrowing Stock
M7	% Change in Money Supply (M3Y)
M8	% Change Gross National Product (Based on 1987 prices)
M9	Monthly Change in Interest Rate Imposed on FX Deposits
M10	Monthly Change in Production Index (Chain-Based)
M11	% Change in Gold Prices
M12	Change in Credit Volume of the Banking Industry (Monthly, %)
M13	Monthly Change Laborforce Index (Manufacturing Industry, Chain-Based)
M14	Income Index Change (Monthly)
M15	FX Rate Index Change (Monthly)
M16	Monthly Change in the Balance of Current Accounts (%)
M17	Consumption Index Change (Monthly)
M18	Monthly Change in Cost of Living Index
M19	Monthly Change in Consumer Confidence Index

2.2. Methodology

At the stage of deriving a multifactor APT model, we first undertook the Kolmogorov-Simirnov Normality Test on the return distribution of each stock to conclude if or not the variable distributions are normal as dictated by most of the linear modeling methods and then applied factor analysis with the Principal Components Analysis and VARIMAX rotation technique on the return data to compute factor scores before carrying out a regression analysis in order to get the final equation that could be used to predict returns. Next, the obtained factor scores uncorrelated with each other then have been used as the predictors to regress returns for each stock and we have consequently constructed 45 separate equations in which factor loads take place as regression coefficients and the factor scores are the values for independent variables. After regressing the geometric mean returns of the stocks on the factor loads, the study has resulted in a final regression equation.

In the procedure of constructing an appropriate single index model based on the CAPM, first of all, a specific beta coefficient (β) for each stock was computed using the entire period firm-specific and market return data with the Equation 5. Afterwards, the vector including the beta scores of the stocks were used to estimate the stock returns through simple regression analysis. Eventually, a regression equation with one explanatory variable (the return on ISE 100 portfolio) has been presented.

The further step in the research is to compare the performance of our APT and CAPM proposals to each other. To make a comparative analysis on their prediction performances, we have employed three measures: Davidson and McKinnon Technique, Posterior Likelihood Ratio, and Forecasting Error Analysis.

Davidson and McKinnon (1981: 781-793) Technique proposes a regression analysis in which the values predicted by the models are being considered independent variables while the actual values are taken as dependent variable and tries to reach an equation as the following:

$$R_i = \alpha R_1 + (1-\alpha) R_2 + e_i \qquad \textbf{(11)}$$

In the Equation 11, R_i is the actual rate of return and α refers to a certain coefficient. R_1 and R_2 simply represent the predicted values generated by each model. The magnitude and significance of the coefficients of R_1 and R_2 give clues about which model is superior. The model with a bigger and statistically significant coefficient is assumed to be better.

The Posterior Likelihood Ratio can be a good criterion provided that the multivariate normality condition is ensured and directly shows which model is more satisfying. The ratio is computed using the following formula (Maddala, 2004: 492)

$$R = \left[\frac{ESS_0}{ESS_1} \right]^{\frac{n}{2}} . n^{\frac{k_0}{k_1}} \qquad \textbf{(12)}$$

In the Equation 12;

R: Likelihood ratio

ESS_i: Sum of squared errors for the model *i*

n: Number of observations

k_i: Number of independent variables included in the model *i*

The case that the ratio is bigger than one suggests that the model coded with 1 has produced better results than those of the model coded with 0.

The analysis of forecasting errors requires the prediction errors of a model be regressed on the independent variables of the other model (Equation 13). The model that can explain the residuals of the other model more accurately (The higher R^2 value, the more accurate model) is assumed to be the best.

$$e_i = \beta_0 + \sum \beta_j . \lambda_j \qquad \textbf{(13)}$$

In the equation, e_i is referred to as forecasting errors, β_j represents regression coefficients, and λ_j is used for the independent variables of the model being tested.

Following the completion of model building and performance comparison processes, the next step is to determine which macroeconomic indicators are most associated with the artificial variables obtained within the scope of the APT model study by using correlation analysis. The macroeconomic indicators that prove to be significantly correlated with the relevant APT factors are selected as proper sources of systematic risk.

During investigating to what extent the models can reflect economic crisis information within their independent variables, the linear discriminant analysis has been used to test the explanatory power of each independent variable over economic crisis conditions. To succeed that, we have divided the whole period into two main parts: the term when the effect of economic crisis is densely experienced, and the term when there is no strong crisis affecting the economy. In dividing the entire period into two parts, we have taken into account the report published by the IMF in 1988 about how long it takes for an economy to recover after any economic crisis. According the findings in that report, it takes approximately 2,6 years for an emerging economy to recover following a crisis (Iseri, 2004: 32). In the light of this fact and also assuming that economic conditions are expected to deteriorate within the same time interval just before an impending economic crisis, we have examined the period between May 1998 and August 2003 (64 months) as the term with the effect of the economic crisis regarding two important economic crisis experienced in Turkey in November 2000 and February 2001. The rest of the period is considered to be free of crisis effects. The months assumed to be not free of crisis effects are assigned a dummy value of 1 while the others are given the value of 0. This set of categorical values has been used as the dependent variable set and put into discriminant analysis along with the independent variable sets of the models which are the factor scores for the APT model and the ISE 100 index return data for CAPM.

The ***linear discriminant analysis*** is a statistical method that basically tries to compute relevant scores to be used in evaluating sample units as being a member of any of the two complementary (binary) groups or cases; for example, failing or non-failing. It is useful for situations where we need to build a predictive model of group membership based on observed characteristics of each case. The procedure generates a discriminant function (or, for more than two groups, a set of discriminant functions) based on linear combinations of the predictor variables that provide the best discrimination between the groups (Equation 14). Dependent variable takes the value of 1 or 0 (may be more than 2 discrete values provided that it is needed to separate sample units into more than 2 groups) according to the actual status of each sample unit. The final score that the technique produces is compared to a certain cut-off point to conclude which group each unit falls into. This cut-off point is defined as the middle point between the means of the units of two case. It can also be computed determining the extreme scores of each group that are generated through a normal probability function (Tatlidil, 1996: 72 - 74). A model that classifies the cases more correctly is assumed to be superior.

$$Y = \sum_{i=1}^{n} w_i X_i \qquad \textbf{(14)}$$

In the equation, Y is the discriminant score, w_i constitutes discriminant coefficient, and X represents predictors.

The linear discriminant technique has some assumptions to simplify the real situation. It matters for the accuracy and reliability of discriminant models whether or not these assumptions are met in real life.

2.3. Hypotheses and Assumptions

In this paper, we argue whether the APT models produce better results as compared to the CAPM and test the hypothesis that the APT model is more accurate than the CAPM. In addition, we also claim that the APT is more robust in reflecting the effects of economic crisis on stock returns.

The assumptions that challenge the reliability of our empirical results are generally composed of the technical requirements of the quantitative techniques we use. Linear modeling studies are always exposed to the theoretical restrictions of the statistical techniques used. Among the restrictive assumptions we are confronted with are the normality condition for variable distributions, absence of multicollinearity among independent variables, linear relationship between dependent and independent variables, constant and homogeneous error terms, no autocorrelation among error terms, stability of factor loads and risk premiums, and so on.

2.4. Empirical Findings and Results

First of all, the return data were tested to ensure whether they show an approximation to a normal distribution with the Kolmogorov Simirnov Normal Distribution Test. The results suggest that the distributions of only two of the stocks can be assumed to be normal and the remaining return distributions including ISE 100 Index Return distribution cannot be judged to be normal, which may negatively affect the accuracy and validity of our model results. The p-value (significance) score is over 0,05 only for three stocks whereas it is below 0,05 for the rest.

2.4.1. APT Model Results

After applying factor analysis on the return data to derive a proper APT function to predict stock returns, the factor scores and factor loads were obtained. The factor analysis results show that the sample is adequate for the analysis at a 94,4 % confidence level (The Kaiser-Meyer-Olkin Measure of Statistical Adequacy statistic proved to be 0,944) which is a value providing strong evidence to claim that it is possible for the distributions to be explained by a factor analysis. Since the significance level for the Bartlett Sphericity Test statistic is below 0,05, it can be claimed that the correlation matrices are consistent for the analysis.

Table 2: **Factor Analysis Sampling Test Results**

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,944
Bartlett's Test of Sphericity	Approx. Chi-Square	4,634E3
	df	990
	Sig.	,000

The results of the factor analysis also show the possibility of explaining the 68,32 % of total variability with five factor for which the Eigenvalue statistic is over 1 (See Table 3).

Table 3: **Total Variance Explained**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance
1	25,627	56,949	56,949	25,627	56,949	56,949	6,131	13,625
2	1,615	3,589	60,538	1,615	3,589	60,538	1,768	3,929
3	1,275	2,833	63,371	1,275	2,833	63,371	1,579	3,508
4	1,169	2,598	65,969	1,169	2,598	65,969	1,552	3,449
5	1,058	2,350	**68,319**	1,058	2,350	68,319	1,552	3,448

The factor scores received for each stock by using the entire-period data were then used as independent variables in predicting the actual rates of return in order to obtain factor loads. In the next phase following the computation of factor loads, we tried to reach a final equation by undertaking a regression analysis on the mean return data (YIELD) and these factor loads. Eventually, the following equation (15) has been derived:

$$E(R_i) = 10,179 + 0,072 b_{i1} - 2,915 b_{i2} - 4,255 b_{i3} - 4,319 b_{i4} - 3,220 b_{i5} \qquad \textbf{(15)}$$

A significance F value of 0,003 makes us 99 % sure that the model is statistically accurate and works (See Table 4). All the factors except Factor 1 prove to be statistically significant at 95 % confidence level but, Factor 1 with the highest capability of explanation cannot be regarded as significant in a statistical manner and on a linear basis (See Table 5). The adjusted coefficient of determination (collective explanation power) of the factors is 0,283, a moderate level of explanation (See Table 6). Expectedly, there is no significant autocorrelation among the error terms because the Durbin Watson Statistic is 2.474[1] (See Table 6)

Table 4: **APT Model ANOVA Results**

ANOVA [b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	32,843	5	6,569	4,471	,003[a]
	Residual	57,296	39	1,469		
	Total	90,138	44			

a. Predictors: (Constant), F5, F4, F3, F1, F2

b. Dependent Variable: YIELD

[1] DW test values are d_{low} = 1,11 and d_{high} = 1.58 for 45 observations (n) and 5 independent variables (k). No autocorrelation because 2,474 > 1,58.

Table 5: **APT Regression Coefficients**

Coefficients [a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	10,179	1,209		8,419	,000		
	F1	,072	1,023	,010	,070	,944	,858	1,165
	F2	-2,915	1,247	-,332	-2,338	,025	,807	1,240
	F3	-4,255	1,242	-,456	-3,425	,001	,922	1,085
	F4	-4,319	1,368	-,464	-3,158	,003	,754	1,326
	F5	-3,220	1,297	-,349	-2,483	,017	,826	1,211

a. Dependent Variable: YIELD

Table 6: **APT Model Summary**

Model Summary [b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change	Durbin-Watson
1	,604[a]	,364	,283	1,21207	,364	4,471	5	39	,003	2,474

a. Predictors: (Constant), F5, F4, F3, F1, F2

b. Dependent Variable: YIELD

2.4.2. CAPM Results

A separate beta coefficient (β_{im}) was calculated for each stock dividing the covariance value between the stock's returns (R_i) and ISE 100 returns (R_m) by the variance of the ISE 100 return distribution in the light of the findings gained through variance-covariance analysis between stock and ISE 100 returns. Regressing the mean rates of return on the beta coefficients, a regression function has been constructed as the following:

$$E\ (R_i) = \alpha_i + R_m\ \beta_i = 4{,}457 + 1{,}796\beta_{im} \quad \textbf{(16)}$$

It can't be claimed that the model is statistically significant at 5 % significance level since the significance F value of the model is 0,068, a value slightly over 0,05 (See Table 7). The independent variable (β) proves not to be statistically significant (See Table 8), and the coefficient of determination of the model is very low, only 7,6 %[2] (See Table 9).

Table 7: **CAPM ANOVA Results**

ANOVA [b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6,817	1	6,817	3,518	,068[a]
	Residual	83,321	43	1,938		
	Total	90,138	44			

a. Predictors: (Constant), BETA

b. Dependent Variable: YIELD

[2] The R^2 value is taken into account to examine the explanatory power of the CAPM model as different from the case for APT model becasue the number of independent variable is only 1 here. Also, there is no need for autocorrelation test.

Table 8: **CAPM Coefficients**

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4,457	,896		4,975	,000		
	BETA	1,796	,958	,275	1,876	,068	1,000	1,000

a. Dependent Variable: YIELD

Table 9: **CAPM Model Summary**

Model Summary[b]

Mode	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,275[a]	,076	,054	1,39202	,076	3,518	1	43	,068	2,062

a. Predictors: (Constant), BETA

b. Dependent Variable: YIELD

The explanatory power of index returns on the changes in stock returns seems to be very low and statistically insignificant.

2.4.3. Comparison on The Performance of the CAPM and APT Models

We can say that the APT model is more accurate and successful in predicting stock returns if considering the R^2 statistics. In other words, it leads us to this conclusion that the APT model has a higher degree of explanatory power (28,3 %) when compared to that of CAPM (5,4 %).

As stated before, the following are the results of the comparisons based on three different approaches: Davidson and McKinnon Technique, Posterior Odds Ratio, and Forecasting Error Analysis.

APT model seems to be more robust in explaining the actual rates of return if regarding the results of the Davidson and McKinnon regression equation we have obtained (Equation 17):

$$R_i = -3,837 + 0,952\, APT_{PREDICTION} + 0,678\, CAPM_{PREDICTION} \quad \textbf{(17)}$$

The finding that the APT predictions have a slightly higher coefficient when compared to that of CAPM means the superiority of APT over CAPM. Moreover, it also convinces us that the APT predictions are statistically significant whereas the CAPM predictions are not (See Table 10). That new regression model in which the predicted values of both models are taken together as independent variables has proved to be a statistically accurate model (See Table 11).

Table 10: **Davidson and McKinnon Regression Results**

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-3,837	2,776		-1,382	,174		
	APT	,952	,201	,575	4,746	,000	,976	1,024
	CAPM	,678	,440	,187	1,540	,131	,976	1,024

a. Dependent Variable: ACTUAL

Table 11: **Davidson and McKinnon Model Accuracy**

ANOVA [b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35,904	2	17,952	13,903	,000[a]
	Residual	54,234	42	1,291		
	Total	90,138	44			

a. Predictors: (Constant), CAPM, APT

b. Dependent Variable: ACTUAL

The expected superiority of APT over CAPM is also proved if taking into account the Posterior Odds Ratio. The ratio for APT against CAPM is 9897,1, a value far bigger than 1 meaning that the APT predictions are more successful[3].

In the case of analyzing forecasting errors, we again observe and prove that the APT model variables (factors) predict the forecasting errors of CAPM more efficiently. The adjusted R^2 value is 0,319 for the APT model against CAPM for which the R^2 value is only 0,03. Besides these, although the explanation of the CAPM errors (CAPMR) by the APT factors can be realized with a statistically significant regression model, it cannot be succeeded in the case that the APT errors (APTR) are being predicted by CAPM (See Tables 12, 13, 14, and 15).

Table 12: **Model Summary - CAPM Errors predicted by APT Factors**

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change	Durbin-Watson
1	,630[a]	,396	,319	1,13541	,396	5,123	5	39	,001	2,443

a. Predictors: (Constant), F5, F4, F3, F1, F2

b. Dependent Variable: CAPMR

[3] $ESS_{APT} = 83,299$ and $ESS_{APT} = 57,25$. For n = 45, $k_{APT} = 5$, and $k_{CAPM} = 1$, $R_{APT\ to\ CAPM} = (83,29 / 57,25)^{45/2} . (45)^{1/5} = 9897,1$

Table 13: **ANOVA Results - CAPM Errors predicted by APT Factors**

ANOVA [b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33,023	5	6,605	5,123	,001[a]
	Residual	50,277	39	1,289		
	Total	83,299	44			

a. Predictors: (Constant), F5, F4, F3, F1, F2

b. Dependent Variable: CAPMR

Table 14: **Model summary - APT Errors predicted by CAPM Factor**

Model Summary [b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,229[a]	,052	,030	1,12327	,052	2,372	1	43	,131	2,443

a. Predictors: (Constant), BETA

b. Dependent Variable: APTR

Table 15: **ANOVA Results - APT Errors predicted by CAPM Factor**

ANOVA [b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,993	1	2,993	2,372	,131[a]
	Residual	54,255	43	1,262		
	Total	57,248	44			

a. Predictors: (Constant), BETA

b. Dependent Variable: APTR

According to the results of our study to match the macroeconomic variables with the five APT factors found significant in the study, no high correlations between the factors and macroeconomic indicators except for ISE 100 index return variable (M1) could be observed. Almost all of the correlations considered significant are at moderate or low levels (See Table 16)

Table 16: **Macroeconomic Variables Matched with APT Factors**

FACTOR	VARIABLES	Pearson CORRELATION	SIGNIFICANCE
1	ISE 100 INDEX	0,733	0,000
2	ISE 100 INDEX	0,488	0,000
	LOG (EXPORT)	0,208	0,031
3	ISE 100 INDEX	0,330	0,001
4	ISE 100 INDEX	0,250	0,000
	INTEREST RATE ON TL-DEPOSITS	0,190	0,049
5	ISE 100 INDEX	0,185	0,048

It is a surprising finding that the major macro variable correlated with the factors is determined as ISE 100 index even though the CAPM results are not satisfactory. The reason why such contradictory results have existed may be the violation in the real life of the basic assumptions that CAPM studies are based on. On the other hand, the TL-deposit interest as an alternative investment parameter rate changes are negatively correlated with the stock return changes (positive correlation with Factor 4 which is negatively correlated with stock returns). It is also an expected situation to get a negative correlation with stock returns for export volume changes. In other words, if a domestic currency is depreciated against strong foreign currencies, the export volume is assumed to increase while stock investments become unattractive because appreciating foreign currencies are perceived as a less risky and better investment alternative.

2.4.4. Testing the Informative Role of CAPM and APT Models During Economic Crises

The results of two discriminant analyses we carried out to test the informative role of the CAPM and APT over economic crisis provide sufficient statistical evidence supporting the claim that APT outperforms CAPM in reflecting the effects of economic crisis on return variation.

Taking into considerations the results of the discriminant analysis based on the APT factors scores, the canonical correlation statistic was computed as 0,218. The same statistic was only 0,173 in the case of analyzing CAPM. In addition, the correct classification rates (classifying the terms as a term with crisis effects or a term free of crisis effects) for APT and CAPM respectively are 64,8 % and 54,6 % (See Table 17 and Table 18)

Table 17: **Correct Classifcation Rates for APT and CAPM**

		MODEL	APT (a)			CAPM (b)		
		CRISIS	Predicted Group Membership		Total	Predicted Group Membership		Total
			0	1		0	1	
Original	Count	0	31	13	44	21	23	44
		1	25	39	64	26	38	64
	%	0	70,5	29,5	100	47,7	52,3	100
		1	39,1	60,9	100	40,6	59,4	100

a. 64,8% of original grouped cases correctly classified. (APT)

b. 54,6 % of the original grouped cases correctly classified. (CAPM)

Table 18: **Canonical Correlation for APT and CAPM**

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
APT	,050	100	100	0,218
CAPM	,018	100	100	0,132

3. Conclusion

There are two competing theories that are used to predict the expected rates of return on stocks; Arbitrage Pricing Theory (APT) and Capital Asset Pricing Models (CAPM). The question on which theory best explains return variation has cast tremendous interest in carrying out studies that could exhibit scientific evidence to favor any of them. In this study that can be considered a typical example of the research done in that field, it is aimed to compare the performance of CAPM and APT models in Turkey especially focusing the informative role of the models about the impending and existing effects of economic crisis on capital markets, merely stock exchanges.

Our results suggest that APT outperforms CAPM in explaining stock return variation and its informative power over crisis events is slightly higher. However, it remains a problem to examine exact macro variables that would best fit the artificial factors derived in APT practices. Other problematic issue that challenges the validity of results and must be dealt with is the need to test the possible impacts of different time and sampling dimensions on results in terms of reliability with the help of panel data analysis and to ensure the conformation with existing modeling assumptions, and so on.

Subsequent studies should address the critical issues mentioned above as well as presenting more robust findings and results that may shed light into the dilemma about the selection of the right theory.

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