Responses of Static and Dynamic Asset Pricing Models to Financial Market Anomalies in Istanbul Stock Exchange

by

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This is to certify that I have examined this copy of a master's thesis by

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To my family

ABSTRACT

This paper documents various explanations for cross-sectional financial market anomalies observed in the Istanbul Stock Exchange. In this framework, we test unconditional and conditional asset pricing models against non-risk firm characteristics by using data on individual securities. In conditional asset pricing models, the factor loadings are allowed to vary with market capitalization, book-to-market ratio and a business cycle indicator. As a business cycle indicator for Turkey, we use the composite leading indicator which is calculated by Central Bank of the Republic of Turkey.

In order to examine the relationship between individual stock returns and non-risk firm characteristics such as size, book-to-market, past returns and liquidity, we apply Fama-Macbeth type regressions in two steps. In the first step, excess stock returns are regressed on factor loadings that vary with size, book-to-market and the macroeconomic variable. Specifically, we use five models: 1) CAPM, 2) Fama-French three factor model, 3) Fama-Frech augmented by momentum factor, 4) Fama-French augmented by illiquidity factor and 5) Fama-French augmented by momentum and illiquidity factor. In the second step, we run cross-sectional regressions in which risk adjusted returns calculated in step 1 are used as dependent variable and regressed on firm specific characteristics. We use monthly returns, and size, book-to-market, past returns and illiquidity for the time period covering February 1997 to April 2008. The results suggest that dynamic versions of multi-factor asset pricing models are able to capture the impact of firm-specific characteristics on expected stock returns but book-to-market effect persists in the static version of all models.
Keywords: Cross-sectional anomalies, Conditional asset pricing models, time-varying beta.

ÖZET

Bu makale İstanbul Menkul Kıymetler Borsası' nda gözlemlenen kesitsel anomalilere çeşitli açıklamalar getirmektedir. Bu çerçevede, hisse senetleri ayrı ayrı ele alınarak, koşullu ve koşulsuz varlık fiyatlama modelleri risk içermeyen şirket özellikleri karşısında test edilmiştir. Koşullu varlık fiyatlama modellerinde, faktör yükleri firmanın piyasa değeri, firmanın defter değerinin piyasa değerine oranı (B/M) ve konjonktür dalgalanmaları göstergesi ile dinamikleştirimiştir. Türkiye için konjonktür dalgalanmaları göstergesi olarak Türkiye Cumhuriyeti Merkez Bankası tarafından belirlenmiş olan Bileşik Öncü Gösterge kullanılmıştır.

Hisse senedi getirileri ile şirket büyüklüğü, B/M, hisse senedinin geçmiş getirileri ve likidite gibi risk içermeyen şirket özellikleri arasındaki ilişkiyi inceleyebilmek için 2 adımdan oluşan Fama-Macbeth regresyonları uygulanmıştır. İlk adımda, getiri fazlalıkları şirket büyüklügü, B/M, ve makroekonomik değişken ile farklılaşan faktör yükleri üzerine regresyon yapılmıştır. Makalede temel olarak şu 5 model kullanılmştır: 1) Finansal Varlıkları Fiyatlama Modeli, 2) Fama-French Üç Faktör Modeli, 3) Momentum faktörü ilaveli Fama-French Modeli, 4) Likidite Faktörü ilaveli Fama-French Modeli, 5) Momentum ve likidite faktörleri ilaveli Fama-French Modeli. İkinci adımda, ilk adımda hesaplanmış olan riski düzeltilmiş getiriler bağımlı değişken olarak alınıp, şirket özellikleri üzerine kesitsel regresyon uygulanmıştır. Şubat 1997 ve Nisan 2008 arasındaki periyoda ait hisse getirisi, şirket büyüklügü, B/M, geçmiş hisse senedi getirileri ve likidite verileri aylık olarak kullanılmıştır. Sonuç olarak, çoklu faktör modellerinin dinamik versiyonları şirket özelliklerinin beklenen getiri üzerindeki etkilerini açıklayabildiği gözlemlenmiştir. Ancak B/M etkisi bütün statik modellerde kalmaya devam etmektedir.

Anahtar Kelimeler: Kesitsel anomaliler, Koşullu varlık fiyatlama modelleri, Zaman değişimli beta.

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Chapter 1

INTRODUCTION

The finance literature offers several asset pricing models to determine the price of an asset. Among these models, classical capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) is the cornerstone of finance for decades. However, CAPM is criticized from two main perspectives. First, CAPM cannot explain the cross-sectional variation in realized stock returns. CAPM measures the risk and explains higher risk with higher beta. However, higher average returns of many investment opportunities cannot be explained by CAPM. Empirical studies over forty years show that CAPM cannot explain following four effects that we focus in this study:

1. Size effect: stocks with small market capitalization outperform stocks with big market capitalization (Banz (1981), Fama and French (1992))

2. Value effect: Stocks with high book-to-market outperform stocks with low book-to-market (Fama and French (1992))

3. Past return: Stocks with higher prior returns continue to outperform stocks with lower prior returns (Jegadeesh and Titman (1993))

4. Illiquidity: Expected stock returns increase with illiquidity (Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Amihud (2002))

In order to explain these effects, multi-factor models are suggested in the place of CAPM. Multi-factor models explain high average returns with factor-mimicking portfolios of these anomalous variables in addition to market return because additional risk factors can be proxies for exposures to systematic risk that cannot be captured by CAPM beta. Fama and French (1993) suggest a three-factor model which includes the market factor, size factor (SMB) and book-to-market factor (HML). SMB (small minus big) is the difference in returns between small and big size firms. HML (high minus low) is the difference in returns of high book-to-market minus low book-to-market firms.

Moreover, CAPM is incorporated with momentum factor because past performance of stocks affects expected stock returns. Therefore, WML (winner minus loser), the momentum factor of Jegadeesh and Titman (1993), is another proxy for exposure to systematic risk. In addition to the proposed powerful factors, Illiquidity factor (Amihud 2002) is suggested as a candidate that can explain cross-sectional variation of average stock returns.

Second, the classical CAPM is static and assumes that risk loadings are stable over time. However, there is considerable variation in measure of risk and risk premium so conditional CAPM is suggested to capture these cross-sectional anomalies. Several empirical studies are conducted to test the performance of conditional CAPM but there are both favorable (Jensen (1968), Dyving and Ross (1985), Jagannathan and Wang (1996), Hansen and Richard (1987)) and unfavorable results (Lewellen and Nagel (2006)). Avramov and Chordia (2006) test also conditional versions of multi-factor models which cannot explain turnover and momentum effect.

Under the consideration of these works, we test static and dynamic versions of single and multi-factor asset pricing models in this paper. Our goal is to evaluate the impact of non-risk firm specific characteristics on expected returns. Following Avramov and Chordia (2006), we would like to provide empirical evidence that supports the innovations in CAPM. We utilize classical CAPM by using ISE 100 as a market factor. Additionally, we test four multi-factor models: Fama-French three factor model, Fama-French augmented by illiquidity, Fama-French augmented by momentum and Fama-French augmented by illiquidity and momentum. SMB and HML factors of Fama-French three factor model are calculated according to Fama and French (1993). WML factor of Jegadeesh and Titman (1993) is considered to be our momentum factor. Finally, our monthly illiquidity factor is based on the measure of Amihud (2002) who designs the illiquidity measure as the average of ratio of absolute daily return to daily volume. We allow factor loadings to vary with size, book-to-market ratio and business cycle predictor, and employ Fama-Macbeth two-stage approach. We estimate five models from individual stock returns and compare the performance of static and dynamic versions of them to explain the impact of firm-specific attributes on expected average returns.

We analyzed several empirical regularities using data from Istanbul Stock Exchange (ISE). Our contribution to the existing literature is three fold. First, to our best knowledge, we are the first to test the performance of both dynamic and static large scale models on ISE so this is the most comprehensive study on cross-sectional anomalies of Turkish stock market. Second, compared to the existing studies on ISE, this is the most updated and extended study. Finally, this is the first study that tests the performance of conditional single factor and multifactor asset pricing models by using individual stocks on ISE instead of portfolios. The use of individual stocks has several advantages over portfolio based models since this method does not suffer from data-snooping bias and loss of information during portfolio formation (Lo and Mackinlay (1990), Litzenberger and Ramaswamy (1979)). All of these characteristics make this study significant for such a developing and leading emerging market.

Our findings show that moving to conditional models increase the explanatory power of all models except CAPM. Not only static CAPM but also three different versions of conditional CAPM are able to capture the book-to-market effect. Even the static versions of four multi-factor models cannot explain the impact of book-to-market on expected returns. Therefore, addition of new factors does not improve the static models. When we move to Fama-French three factor model, only the model scaled with size and book-to-market gives us insignificant results. The predictive power of book-to-market ratio is unexplained by Fama-French three factor scaled by size, book-to-market and business cycle predictor. However, the four factor models conditioned with size, book-to-market and business cycle predictor provides an improvement and capture all firm specific attributes. In sum, the impact of non-risk firm characteristics on stock returns in ISE are explained by the models we test in this study so we provide empirical evidence that supports the innovations in CAPM.

The paper is organized as follows. Section 2 details the prior studies in literature. Section 3 details the empirical methodologies used in this paper. Section 4 describes the data and summarizes the institutional characteristics of ISE. Results are presented in Section 5. Concluding remarks are offered in the last section.

Chapter 2

LITERATURE REVIEW

In its simplest form, the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) states that average asset returns are linearly related to market beta and market beta is able to explain the cross-section of expected returns. Fama and Macbeth (1973) provide empirical support for this fundamental model and do not find any evidence for misspecification. Their analysis for the pre-1969 period points out the positive relation between market beta and average return. However, CAPM is not able to capture the cross-sectional variation of average stock returns. Therefore, the failure of CAPM triggered a vast interest in models with better pricing abilities to capture cross-sectional anomalies such as size, book-to-market, past return and liquidity. To analyze these anomalies, prior studies suggest additional risk factors that are defined as the return of portfolios formed according to cross-sectional sorts. In addition to omitted factor problem, static nature of CAPM is considered to be another reason for these anomalies so conditional models are suggested.

The size effect literature is started by Banz (1981) who finds that higher returns of stocks with small market capitalization cannot be explained only by their estimated beta. Additionally, Fama and French (1993) advocate that factor-mimicking portfolios of size and book-to-market have ability to explain the cross-sectional variation of average returns that cannot be captured solely by the overall market factor. The suggested additional two factors which are SMB, long in small size portfolio and short in big size portfolio and HML, long in high B/M portfolio and short in low B/M portfolio offer higher return than the average.

In the empirical finance literature, past return anomalies are defined as momentum and reversal. Momentum means that winners continue to be winner and loser continue to be loser. On the other hand, reversal is a counterpart of momentum and means that past losers perform well while past winners do badly. Debondt and Thaler (1985) document the long-run reversal. They report an average return of 25% over three years by using contrarian strategy which means buying past losers and selling past winners. On the other hand, Jegadeesh (1990) finds that abnormal returns of about 2.5% per month can be generated by short-term reversal strategy of individual stocks. Following this work, Jegadeesh and Titman (1993) shows that momentum cannot be explained by market risk. They assert that portfolios performed better in the past continue to offer higher returns in the future. Buying portfolios with high returns and selling portfolios with low returns over the previous 3 to 12 months generate the return of about 1% per month. Because of this relationship between cross-sectional variation of return and past return, they suggested WML, long in winner portfolio and short in loser portfolio, as a predictive factor.

In addition, liquidity is considered to affect asset returns. However, there are several measures of liquidity in literature because liquidity is easy to observe but difficult to define. Therefore, as a result of alternative proxies for liquidity level, different results are observed in the literature. Amihud and Mendelson (1986) find a positive relationship between expected stock returns and their illiquidity measure which is characterized by bid-ask spread. On the other hand, Brennan and Subrahmanyam (1996) define illiquidity measure as price impact and also report a positive impact on stock returns. Amihud (2002) suggest an illiquidity measure to verify that cross-sectional variation in average returns are influenced by illiquidity. This measure is formed as the average ratio of daily absolute return to the dollar trading volume on that day. Recently, liquidity measure is suggested as a source of priced risk because investors demand higher returns when market liquidity decreases. Pastor and Stambaugh (2003) find that higher the stock sensitivity to aggregate liquidity higher the expected return. Employing this strategy generates 7.5% annual premium. Acharya and Pedersen (2005) develop an illiquidity adjusted CAPM by using Amihud (2002) illiquidity measure. Their model is better than CAPM and gives 1% annual premium.

Apart from the missing factor problem, CAPM assumes that risk loadings are stable even though there is a considerable variation in measure of risk and risk premium. The ignorance of risk dynamics that causes the misspecification motivates the development of dynamic CAPM. Jensen (1968), Dyving and Ross (1985), and Jagannathan and Wang (1996) show that conditional CAPM works period by period. Additionally, Hansen and Richard (1987) conditional CAPM could hold perfectly while the static one fails. On the other hand, Lewellen and Nagel (2006) report that the conditional CAPM does not outperform the unconditional CAPM. Moreover, many conditional multi-factor models are suggested by previous studies but not all of them are able to reach conclusive results. Ferson and Harvey (1999) put forward the explanatory power of lagged economy-wide variables to explain the cross-section of expected returns. They find that three-factor model conditioned with macroeconomic variables has explanatory power on size and B/M sorted portfolios. Gomes, Kogan and Zhang (2003) show that size and book-to-market is able to explain cross-sectional variation because of their correlation with conditional market beta. On the other hand, Ghysels (1998) advocates that the pricing errors in most of the cases of conditional asset pricing models are higher than the pricing errors in constant beta models. Brennan, Chordia and Subrahmanyam (1998) show the relation between cross-sectional variation in stock returns and firm attributes by using the risk-adjusted return calculated in the time-series step of Fama-Macbeth procedure. Extending the method in Brennan, Chordia and Subrahmanyam (1998), Avramov and Chordia (2006) assert that the impact of momentum and turnover cannot be captured by conditional versions of multifactor models while size and book-to-market can be.

Chapter 3

METHODOLOGY

While testing the performance of conditional and unconditional versions of five asset pricing models-1) CAPM 2) Fama-French three factor model 3) Fama-Frech augmented by momentum factor 4) Fama-French augmented by illiquidity factor 5) Fama-French augmented by momentum and illiquidity factor-, we use the methodology based on Brennan, Chordia and Subrahmanyam (1998) and Avramov and Chordia (2006). The methods utilized to calculate risk factors that are used in five asset pricing models are consistent with the prior studies.

3.1 Preliminaries

Sharpe (1964) and Lintner (1965) introduced risk-return model CAPM which includes a single factor, market risk factor:

$$r_{it} = \alpha_i + \beta_{1i} MKT_t + \epsilon_{it}. \tag{3.1}$$

where r_{it} is the excess return of asset i and MKT_t is excess market return. In this framework, the ISE 100 index, weighted by market capitalization of the 100 biggest companies' stocks, is employed as a market return for all five models because it is considered to be a determining measure for the Turkish stock market.

In the second model, Fama-French three factor model, two factors, SMB(Small minus Big) and HML(High minus Low), are proposed in addition to market return of CAPM:

$$r_{it} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \epsilon_{it}. \tag{3.2}$$

where SMB_t is the return of SMB portfolio and HML_t is the return of HML portfolio. These factors for Istanbul Stock Exchange are designed by using exactly the same method described in Fama and French (1993). SMB is defined as the difference between the average of high, medium and low book-to-market portfolio returns with small market capitalization and the average of high, medium and low book-to-market portfolio returns with big market capitalization. HML is constructed as difference between the average of small and big market capitalization portfolio returns with high book-to-market ratio and the average of small and big market capitalization portfolio returns with low book-to-market ratio. To sum up, Fama and French advocates that growth and value portfolios offers higher return than the average.

In this work, as a fourth factor we add illiquidity or momentum to the Fama-French three factor model, and test Fama-French augmented by illiquidity factor model and Fama-French augmented by momentum factor model. First four-factor model, Fama-French augmented by an illiquidity factor, includes an illiquidity factor in addition to the three factors of Fama-French model:

$$r_{it} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} ILLIQ_t + \epsilon_{it}. \tag{3.3}$$

In this formula, $ILLIQ_t$ is created according to Amihud (2002):

$$ILLIQ_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|R_{imd}|}{VOL_{imd}}. \tag{3.4}$$

where D_{im} is the number of trading days for stock i in month m (for annual illiquidity measure D_{im} is the number of days in year m), R_{imd} is the return of stock i on day d of month m and VOL_{iyd} is the volume of stock i on day d of month m. We calculate both 1 month illiquidity and 1 year illiquidity factors and then select the most significant one, which is 1 month illiquidity, as a candidate measure of illiquidity effect. After sorting stocks according to this monthly illiquidity measure, we form ten value-weighted monthly illiquidity portfolios and calculate the illiquidity factor as the difference between the monthly return of portfolio with the lowest illiquidity and the monthly return of portfolio with the highest illiquidity.

Second four-factor model, Fama-French augmented by a momentum factor, includes WML (winner minus loser) as a momentum factor:

$$r_{it} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} WML_t + \epsilon_{it}. \tag{3.5}$$

By taking into account the criterion in Jegadeesh and Titman (1993), we calculate WML (Winner Minus Loser) factor. which is based on lagged 6 months return because after estimating all factors (lagged 1, 3, 6 and 12 months return) described in Jegadeesh and Titman (1993), we select the most significant factor as a possible proxy for momentum effect. For each month, by looking at the lagged 6 months return of a stock we sort all trading stocks and form ten portfolios. The portfolio with the lowest return is named as loser and the portfolio with the highest return is named as winner. Then, we track these winner and loser portfolios next 6 months and calculate 6 months returns to obtain WML factor. Briefly, Jegadeesh and Titman (1993) documents that winners continue to be winners and losers continue to be losers.

Finally, as a five-factor model we test Fama-French augmented by an illiquidity factor and a momentum factor:

$$r_{it} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} ILLIQ_t + \beta_{5i} WML_t + \epsilon_{it}. \tag{3.6}$$

where the $ILLIQ_t$ and MOM_t is as defined before.

The close form of K factor model can be written as:

$$r_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ki} F_{kt} + \epsilon_{it}. \tag{3.7}$$

where F_{kt} is the monthly return of factor k. This formula basically gives us the static form of these single-factor and multi-factor models since β_{ki} is constant and does not respond to conditioning information. However, as implied in prior studies,information available at time t tells us much about anomalies. Therefore, these static betas can be conditioned with some exogenous variables according to the previous studies as written in equation (4.8).

$$r_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{kit-1} F_{kt} + \epsilon_{it}. \tag{3.8}$$

In general, β_{kit-1} is a linear function of exogenous variables. This equation can be written as in (4.9) for single-factor CAPM:

$$r_{it} = \alpha_i + \beta_{1it-1} MKT_t + \epsilon_{it}. \tag{3.9}$$

While testing these one single-factor model and four multi-factor models, we basically follow two-stage test of Fama-Macbeth (1973) which consists of time-series analysis in the first step and cross-sectional analysis in the second step. This two-step procedure is appropriate at this point because risk premium, expected return and factor loadings cannot be observed.

3.2 Risk-adjusted Returns

We conduct our tests in the first step according to the full sample analysis method described in the data part. The beta of factor k for month (t-1) in the single and multi-factor models is characterized as follows:

$$\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + (\delta_{ki3} + \delta_{ki4} z_{t-1}) Size_{it-1} + (\delta_{ki5} + \delta_{ki6} z_{it-1}) + BM_{it-1}. \tag{3.10}$$

$Size_{it-1}$:market capitalization of stock i in month t-1

BM_{it-1} :book-to-market ratio of stock i in month t-1

z_{t-1} :value of business cycle predictor in month t-1

As observed in the formula above, the beta of each factor in any model is varying with three variables, size, book-to-market ratio and macroeconomic variable. All models are tested by using individual stocks so beta for each factor is characterized at stock level. In addition, based on this formula we test four hypotheses in order to obtain one unconditional and three different conditional models that can help us to test whether various conditioning information can be beneficial to price assets appropriately. The four hypotheses are as follows:

$$H_1 : \delta_{ki2} = \delta_{ki3} = \delta_{i4} = \delta_{ki5} = \delta_{ki6} = 0$$
$$H_2 : \delta_{ki2} = \delta_{ki4} = \delta_{ki6} = 0$$
$$H_3 : \delta_{ki3} = \delta_{ki4} = \delta_{ki5} = \delta_{ki6} = 0$$
$$H_4 : \delta_{kin} \neq 0, n = 1, 2, ..., 6$$

If we rewrite β_{kit-1} according to these four hypotheses, we obtain the following, respectively:

$$H_1 : \beta_{kit-1} = \delta_{ki1}$$
$$H_2 : \beta_{kit-1} = \delta_{ki1} + \delta_{ki3} Size_{it-1} + \delta_{ki5} BM_{it-1}$$
$$H_3 : \beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$$
$$H_4 : \beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$$

The first hypothesis gives us the static version of single factor and multi-factor models because the factor loading β_{kit-1} is not time-varying. The other three are varying with size, book-to-market ratio or business cycle predictor.

We also do robustness checks for the time series regression part by using dummy variable for the financial crisis of Turkey and raw returns instead of excess returns.

3.3 Regressions

In the second stage, we run 9 cross-sectional regressions by including five firm-specific characteristics which are size, book-to-market, lagged 1 month return, lagged 6 months return and 1 month illiquidity to investigate the predictive ability of these non-risk firm characteristics in the cross-section of stock returns. We choose these non-risk firm characteristics because they are verified to have explanatory power by previous studies.

In Fama-Macbeth two step procedure the betas calculated with error in time-series regressions are included in cross-sectional regressions as independent variables. Typically, this causes error-in-variable problem in two-step procedure of Fama-Macbeth. However, we try to eliminate this problem as defined in Brennan, Chordia and Subrahmanyam (1998) and Avramov and Chordia (2006). The risk-adjusted return in (3.11) obtained from time-series regressions as the sum of intercept and error term is used in cross-sectional regressions as dependent variable. By excluding betas from the set of regressors, we can avoid error-in-variables problem partially.

$$R_{it}^{*} = \alpha_i + \epsilon_{it}. \tag{3.11}$$

$$R_{it}^{*} = c_{0t} + c_{1t}Size_{it-1} + c_{2t}BM_{it-1} + c_{3t}Past1_{it-1} + c_{4t}Past6_{it-1} + c_{5t}Illiq_{it-1} + u_{it}. \tag{3.12}$$

where

$Size_{it-1}$:market capitalization of stock i in month t-1

BM_{it-1} :book-to-market ratio of stock i in month t-1

$Past1_{it-1}$:lagged 1 month return of stock i in month t-1

$Past6_{it-1}$:lagged 6 months return of stock i in month t-1

$Illiq_{it-1}$:1 month illiquidity of stock i in month t-1

Investors can make their investment decisions according to the available data at the beginning of month t. Therefore, as observed from (3.12), we use the value of firm characteristics in the previous month for the regression of risk adjusted return in month t.

Chapter 4

DATA

The analyzed asset pricing models use monthly data of individual stocks in ISE from February 1997 to April 2008 so the whole data includes observations of 396 different stocks for 135 months. However, we exclude "Investment Trusts" and "Real Estate Investment Trusts" from our sample. The monthly returns are compounded from daily adjusted close YTL prices of individual stocks. However, our regression sample for each month does not consist of all of the stocks traded in the corresponding month. In order to be included in regression sample, trading data of a stock should be available for at least 60 months of 135 months. If a stock satisfies this condition, we also control the availability of size, book-to-market, lagged return and illiquidity data of this stock in month t-1 for the month t.

Table 4.1: Descriptive Statistics

This table represents the time series averages of cross-sectional means, medians, standard deviations,1%, 2.5%, 97.5% and 99% percentiles for an average of 224 ISE stocks over 130 months from July 1997 to April 2008.

	Mean	Median	Standard dev.	1%	2.5%	97.5%	99%
Firm Size (billions)	0.405	0.065	1.192	0.004	0.006	3.752	6.578
Book-to-market ratio	0.757	0.616	0.635	0.061	0.108	2.184	2.867
Past 1 month return	0.039	0.013	0.168	-0.248	-0.193	0.427	0.593
Past 3 month return	0.026	0.015	0.088	-0.151	-0.115	0.224	0.295
Past 6 month return	0.024	0.018	0.060	-0.099	-0.075	0.155	0.197
1 Month illiquidity	7.737	0.232	58.953	0.002	0.003	44.848	130.927

As seen in Table 4.1, we look at the statistics of the available data and report the time-series averages of the cross-sectional means, medians, standard deviations,1% percentile, 2.5% percentile, 97.5% percentile and 99% percentile of the stock characteristics used in the regression analyses.

To decrease the effect of outliers on the results of regression analysis, we winsorize the data of size, book-to-market, 1 month lagged return, 6 month lagged return and monthly illiquidity. While winsorizing the data, we equalize values which are greater than 97.5% percentile to the value of 97.5 percentile. Moreover, the values less than 2.5% percentile are set equal to the value of 2.5% percentile. Additionally, as observed from Table 4.1, there is substantial skewness in data so we take the logarithmic transformations of winsorizing data. We employ winsorizing to all six variables but we take log transformations of only size, book-to-market ratio and illiquidity because the lagged return data consists of negative values.

4.1 Characteristics of ISE

Istanbul Stock Exchange (ISE), a leading emerging market, operates since 1986 but attracts more and more investor interest because of its dynamic and developing structure. The annual value of shares traded US$ 252 billion as of 2008 makes ISE the tenth largest stock market if compared to the Europe, Africa and Middle East stock exchanges according to the statistics of World Federation of Exchanges. The share of foreign investment became $\%56$ of free float of shares in 2008. With a totally computerized and regularized system makes ISE more attractive for foreign investors so Furthermore, the market capitalization of ISE is US$ 118 billion with 317 equity shares listed at the end of 2008. All these statistics show that ISE is the second largest stock exchange among emerging markets and ISE becomes more attractive than various emerging markets.

Chapter 5

EMPIRICAL RESULTS

While assessing the empirical results of one unconditional and three conditional versions of five different asset pricing models, we look at the t-ratio calculated according to the method defined in Fama and Macbeth (1973). In the second step of Fama-Macbeth procedure, we run monthly cross-sectional regressions in (3.12) to obtain time-series of the coefficient estimates. As written in (5.1), to calculate the t-ratio of j^{th} independent variable we divide the time-series average of monthly coefficient estimates by the standard error of mean.

$$t(c_j) = \frac{\frac{1}{T}\sum_{t=1}^{T}\hat{c}_{jt}}{\sigma(\hat{c}_{jt})}, j = 0, ..., 5. \tag{5.1}$$

The t-ratios acquired by the help of this method are preferred to the t-ratios obtained from the regression because we encounter high level correlation across stock returns in each month. In this framework, the measure of asset pricing models' explanatory power is derived and evaluated. If an asset pricing model has ability to explain the effect of firm specific characteristics, this measure for each firm characteristic should be insignificant.

We follow this procedure for each asset pricing model and tabularize the findings of nine cross-sectional regressions of risk adjusted returns on intercept and five firm specific attributes.In order to observe the influence of each attribute, these five attributes and intercept are included to the regression model one by one. To report the level of pricing error in the cross-section regression step, we run the regression of risk-adjusted return on only constant. Furthermore, we have a dummy variable for the financial crisis periods of Turkey as an independent variable since we want to guard against the unusual effect of surprisingly high level of risk-free rate during these periods. We also report the time-series average of $\bar{R}^2$ to examine the performance of model. Under these empirical results, insignificant Fama-Macbeth estimates with low $\bar{R}^2$ mean that model fails the capture the impact of specific firm-characteristic on average return. Robustness checks are done also without financial crisis dummy by using excess return and raw return, and the results of robustness checks can be found in the appendix.

5.1 CAPM

Table 5.1 documents four panels for each of the hypotheses utilized to form static and dynamic versions of CAPM. Panel 1 of this table summarizes Fama-Macbeth coefficient estimates of nine cross-sectional regressions for static CAPM model. Size cannot be captured by static single factor model when only size and intercept are included to the cross-sectional regression. However, when other firm-level variables embraced to the regression, size can be explained by model. On the other hand, none of the cross sectional regressions designed for static CAPM is able to capture the B/M effect. The predictive power of past 6 months return cannot be explained by none of examined CAPM versions but inclusion of other firm characteristics improve the model.

Furthermore, if three different dynamic versions of CAPM in Panel 2, Panel 3 and Panel 4 are examined, then we confront exactly the same scenario as in the static one. However, the $\bar{R}^2$ of the models scaled by size and book-to-market ratio is lower than the unscaled one so we can imply that models conditioned on size and book-to-market ratio perform better than the unconditional one. As a result, the time-varying versions of CAPM do not make any contribution to explanatory power of the static model because the uncaptured firm characteristics in unconditional model stay unexplained in conditional models. Ultimately, we suggested additional models to capture the impact of unexplained firm attributesn.

5.2 Fama-French Three Factor Model

In the time-series regression step, three time-varying betas are characterized for three factors, MKT, SMB and HML, and the risk adjusted returns are calculated as defined above. The Fama-Macbeth coefficient estimates obtained as a result of cross-sectional regressions of risk-adjusted returns on firm-level variables are summarized in Table 5.2. Similar to the findings of CAPM, static versions of Fama-French three factor model cannot explain the predictive power of B/M.

Table 5.1: Fama-Macbeth estimates in CAPM

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 1: $\beta_{kit-1} = \delta_{ki1}$							
CSR 0	0.009						0.000
	1.978						
CSR 1	0.067	-0.003					0.022
	2.346	-2.289					
CSR 2	0.016		0.010				0.013
	2.653		4.505				
CSR 3	0.005			-0.015	-0.086		0.034
	0.736			-0.944	-2.250		
CSR 4	0.012					0.001	0.012
	2.141					1.515	
CSR 5	0.042	-0.002	0.008				0.031
	1.483	-1.106	3.970				
CSR 6	0.027	-0.001	0.008	-0.013	-0.044		0.060
	0.981	-0.695	3.744	-0.864	-1.289		
CSR 7	0.037	-0.001	0.008			0.001	0.041
	1.207	-0.748	4.064			0.709	
CSR 8	0.021	-0.001	0.008	-0.013	-0.045	0.001	0.071
	0.722	-0.361	3.776	-0.872	-1.270	0.970	
Panel 2: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki3} Size_{it-1} + \delta_{ki5} BM_{it-1}$							
CSR 0	0.008						0.000
	1.832						
CSR 1	0.067	-0.003					0.022
	2.379	-2.361					
CSR 2	0.015		0.010				0.012
	2.555		4.423				
CSR 3	0.004			-0.012	-0.080		0.032
	0.610			-0.787	-2.230		
CSR 4	0.011					0.001	0.012
	2.069					1.695	
CSR 5	0.045	-0.002	0.007				0.030
	1.609	-1.291	3.768				
CSR 6	0.029	-0.001	0.007	-0.011	-0.041		0.058
	1.096	-0.899	3.439	-0.724	-1.269		
CSR 7	0.040	-0.001	0.008			0.001	0.041
	1.333	-0.917	3.841			0.808	
CSR 8	0.023	-0.001	0.007	-0.011	-0.041	0.001	0.069
	0.808	-0.511	3.492	-0.722	-1.249	1.104	

Table 5.1 (Continued)

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 3: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$							
CSR 0	0.009						0.000
	1.972						
CSR 1	0.065	-0.003					0.022
	2.284	-2.217					
CSR 2	0.016		0.010				0.012
	2.607		4.382				
CSR 3	0.003			-0.012	-0.077		0.035
	0.526			-0.775	-2.111		
CSR 4	0.012					0.001	0.012
	2.140					1.501	
CSR 5	0.042	-0.002	0.008				0.031
	1.471	-1.108	3.831				
CSR 6	0.026	-0.001	0.007	-0.011	-0.037		0.061
	0.951	-0.733	3.720	-0.708	-1.137		
CSR 7	0.038	-0.001	0.008			0.001	0.041
	1.232	-0.792	3.899			0.689	
CSR 8	0.020	-0.001	0.007	-0.011	-0.038	0.001	0.071
	0.683	-0.386	3.742	-0.717	-1.134	0.979	
Panel 4: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$							
CSR 0	0.008						0.000
	1.780						
CSR 1	0.061	-0.003					0.021
	2.251	-2.230					
CSR 2	0.014		0.009				0.012
	2.373		4.033				
CSR 3	0.002			-0.008	-0.069		0.033
	0.363			-0.569	-2.078		
CSR 4	0.011					0.001	0.011
	2.002					1.671	
CSR 5	0.042	-0.002	0.007				0.029
	1.564	-1.286	3.420				
CSR 6	0.030	-0.001	0.006	-0.007	-0.032		0.058
	1.155	-1.067	3.198	-0.490	-1.083		
CSR 7	0.037	-0.001	0.007			0.001	0.039
	1.284	-0.901	3.418			0.845	
CSR 8	0.024	-0.001	0.006	-0.007	-0.033	0.001	0.068
	0.833	-0.629	3.188	-0.485	-1.092	1.048	

Nevertheless, when the betas of each factor are allowed to vary with size and book-to-market ratio, the model becomes more robust and gains an explanatory power for the impact of B/M. Therefore, unlike CAPM, Fama-French three factor model can be improved by scaling factor loadings with size and book-to-market, as seen in Panel 2 of Table 5.2. Moreover, comparing the results in Panel 2 and Panel 4 of Table 5.2, scaling with business cycle predictor in addition to size and B/M does not help to explain the book-to-market effect so the predictive power of the conditional model decreased with business cycle predictor. Note that, $\bar{R}^2$ value in all versions of Fama-French model is lower than those in the corresponding version of CAPM. With the support of the R^2 value, Fama-French three factor model outperform the CAPM.

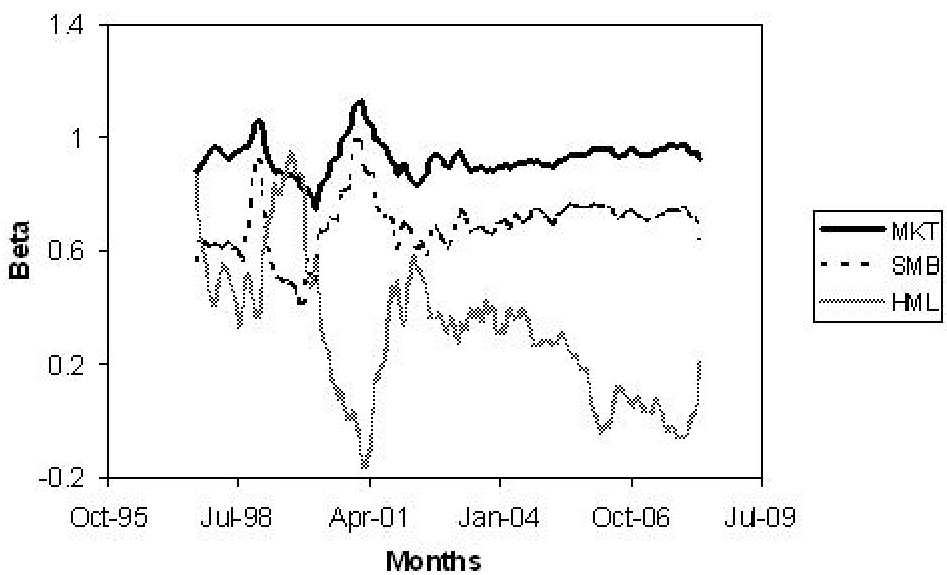

Figure 5.2.1: FF loadings

In order to find the reason why conditional Fama-French three-factor model is able to explain book-to-market ratio effect when scaled with size and book-to-market, we look at the factor loadings of market excess return, SMB and HML. As seen in Figure 5.2.1, there is time-varition in factor loadings. Moreover, the loadings of SMB and market have very similar patterns and follow

Table 5.2: Fama-Macbeth estimates in FF Three-Factor Model

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 1: $\beta_{kit-1} = \delta_{ki1}$							
CSR 0	0.003						0.000
	1.643						
CSR 1	0.047	-0.003					0.005
	4.107	-3.974					
CSR 2	0.008		0.008				0.007
	3.551		4.612				
CSR 3	0.000			-0.013	-0.071		0.030
	0.014			-0.862	-2.118		
CSR 4	0.006					0.001	0.009
	2.086					1.886	
CSR 5	0.028	-0.001	0.006				0.011
	2.393	-1.905	3.541				
CSR 6	0.015	-0.001	0.005	-0.013	-0.045		0.040
	1.171	-0.920	3.134	-0.885	-1.362		
CSR 7	0.020	-0.001	0.007			0.001	0.022
	1.347	-0.737	3.733			1.161	
CSR 8	0.007	0.000	0.006	-0.013	-0.047	0.001	0.051
	0.438	-0.136	3.218	-0.878	-1.379	1.345	
Panel 2: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki3} Size_{it-1} + \delta_{ki5} BM_{it-1}$							
CSR 0	0.003						0.000
	1.814						
CSR 1	0.042	-0.002					0.005
	3.726	-3.571					
CSR 2	0.007		0.005				0.005
	3.294		3.460				
CSR 3	-0.001			-0.005	-0.033		0.027
	-0.368			-0.378	-1.118		
CSR 4	0.006					0.001	0.009
	2.435					2.197	
CSR 5	0.032	-0.001	0.004				0.010
	2.670	-2.232	2.248				
CSR 6	0.021	-0.001	0.003	-0.006	-0.012		0.037
	1.540	-1.497	1.703	-0.406	-0.401		
CSR 7	0.024	-0.001	0.004			0.001	0.020
	1.690	-1.098	2.334			1.326	
CSR 8	0.011	-0.001	0.003	-0.006	-0.015	0.001	0.048
	0.710	-0.557	1.806	-0.417	-0.473	1.621	

Table 5.2 (Continued)

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 3: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$							
CSR 0	0.003						0.000
	1.551						
CSR 1	0.042	-0.002					0.005
	3.720	-3.567					
CSR 2	0.007		0.007				0.007
	3.268		4.236				
CSR 3	-0.001			-0.002	-0.065		0.031
	-0.147			-0.144	-2.041		
CSR 4	0.005					0.001	0.009
	1.995					1.719	
CSR 5	0.025	-0.001	0.006				0.012
	2.120	-1.655	3.287				
CSR 6	0.015	-0.001	0.005	-0.002	-0.039		0.042
	1.205	-1.034	3.063	-0.135	-1.264		
CSR 7	0.017	-0.001	0.006			0.001	0.022
	1.184	-0.606	3.470			1.118	
CSR 8	0.007	0.000	0.005	-0.002	-0.041	0.001	0.053
	0.473	-0.233	3.160	-0.124	-1.274	1.291	
Panel 4: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$							
CSR 0	0.000						0.000
	-0.063						
CSR 1	0.043	-0.002					0.005
	4.002	-4.146					
CSR 2	0.005		0.008				0.007
	2.606		6.085				
CSR 3	-0.004			-0.002	-0.077		0.031
	-1.161			-0.161	-2.774		
CSR 4	0.001					0.001	0.009
	0.491					1.174	
CSR 5	0.022	-0.001	0.007				0.011
	1.971	-1.591	4.916				
CSR 6	0.017	-0.001	0.007	-0.002	-0.046		0.042
	1.308	-1.271	4.292	-0.173	-1.647		
CSR 7	0.016	-0.001	0.007			0.001	0.022
	1.192	-0.744	5.004			0.708	
CSR 8	0.007	0.000	0.007	-0.003	-0.049	0.001	0.053
	0.458	-0.370	4.445	-0.214	-1.708	1.020	

an increasing pattern during recessions period of Turkey. On the other hand, HML behaves in an opposite way.

On the other hand, as displayed in all panels of Table 5.2, the past 1 month and past 6 months return have insignificant results when all firm attributes are included to the model so in contrast to Fama and French (1996), three-factor model can capture the momentum effect on expected returns in Turkish stock market.

5.3 Fama-French Augmented by an Illiquidity Factor

Up to this point, neither the three-factor model conditioned with business cycle predictor nor unconditional versions of both three-factor model and CAPM is able to capture the impact of book-to-market on expected returns so we test the predictive power of four-factor model, Fama-French augmented by an illiquidity factor.

Table 5.3 reports the cross-sectional regression results of this four-factor model. The unconditional model explain size, past 1 month return, past 6 months return and illiquidity effect but cannot capture the book-to-market effect as unconditional version of Fama-French three factor model does so we can conclude that as a fourth factor illiquidity cannot improve the explanatory power of Fama-French unconditional model. Additionally, the effect of size and past 6 months return cannot be captured by the static model if these variables stand alone in the cross-sectional regression model. However, the largest cross-sectional regression model consists of all firm attributes can easily capture these characteristics. When beta is allowed vary with size and book-to-market ratio, as observed in Fama-French three factor model, the impact of all firm characteristics are captured. In a similar way, conditioning beta on business cycle predictor does not make any contribution to the Fama-French three factor model. On the other hand, the last specification, conditioning beta on size, book-to-market ratio return and business cycle predictor substantially improves the explanatory power of Fama-French model. Note also that the $\bar{R}^2$ of this model is lowered with incorporation of illiquidity factor. To sum up, while Fama-French three factor model with the same specification cannot capture book-to-market effect, this model is able to explain all attributes. In other words, inclusion of illiquidity factor makes huge contributions to the three factor model.

Table 5.3: Fama-Macbeth estimates in FF plus illiquidity

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 1:$\beta_{kit-1} = \delta_{ki1}$							
CSR 0	0.005						0.000
	2.878						
CSR 1	0.044	-0.002					0.005
	3.889	-3.665					
CSR 2	0.008		0.007				0.006
	4.264		4.226				
CSR 3	0.002			-0.014	-0.065		0.029
	0.519			-0.990	-1.939		
CSR 4	0.007					0.001	0.008
	3.195					2.056	
CSR 5	0.027	-0.001	0.006				0.011
	2.285	-1.718	3.214				
CSR 6	0.016	-0.001	0.005	-0.015	-0.042		0.040
	1.219	-0.894	2.701	-1.006	-1.259		
CSR 7	0.015	0.000	0.006			0.001	0.020
	1.097	-0.394	3.467			1.494	
CSR 8	0.004	0.000	0.005	-0.015	-0.043	0.001	0.049
	0.251	0.128	2.879	-0.998	-1.270	1.751	
Panel 2: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki3}Size_{it-1} + \delta_{ki5}BM_{it-1}$							
CSR 0	0.005						0.000
	2.958						
CSR 1	0.038	-0.002					0.005
	3.487	-3.236					
CSR 2	0.007		0.004				0.006
	3.703		2.736				
CSR 3	0.001			-0.004	-0.021		0.027
	0.200			-0.337	-0.708		
CSR 4	0.008					0.001	0.008
	3.600					2.317	
CSR 5	0.031	-0.001	0.002				0.010
	2.660	-2.201	1.600				
CSR 6	0.023	-0.001	0.002	-0.005	-0.004		0.037
	1.755	-1.669	1.089	-0.388	-0.122		
CSR 7	0.023	-0.001	0.003			0.001	0.019
	1.721	-1.105	1.652			1.447	
CSR 8	0.014	-0.001	0.002	-0.006	-0.005	0.001	0.047
	0.883	-0.704	1.197	-0.421	-0.161	1.774	

Table 5.3 (Continued)

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 3: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$							
CSR 0	0.005						0.000
	2.805						
CSR 1	0.038	-0.002					0.005
	3.506	-3.233					
CSR 2	0.008		0.006				0.007
	4.015		3.741				
CSR 3	0.002			-0.003	-0.061		0.031
	0.563			-0.208	-1.904		
CSR 4	0.007					0.001	0.008
	3.149					1.922	
CSR 5	0.023	-0.001	0.005				0.011
	2.042	-1.476	2.818				
CSR 6	0.018	-0.001	0.004	-0.003	-0.039		0.042
	1.372	-1.073	2.551	-0.191	-1.218		
CSR 7	0.013	0.000	0.005			0.001	0.020
	0.924	-0.239	3.067			1.496	
CSR 8	0.006	0.000	0.005	-0.003	-0.040	0.001	0.051
	0.382	-0.023	2.751	-0.199	-1.246	1.701	
Panel 4: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$							
CSR 0	0.004						0.000
	2.858						
CSR 1	0.022	-0.001					0.004
	2.228	-1.918					
CSR 2	0.006		0.003				0.005
	3.383		2.182				
CSR 3	0.002			0.009	-0.020		0.031
	0.555			0.671	-0.716		
CSR 4	0.006					0.001	0.008
	3.100					1.511	
CSR 5	0.017	-0.001	0.002				0.010
	1.518	-1.100	1.444				
CSR 6	0.017	-0.001	0.002	0.008	-0.004		0.042
	1.354	-1.219	1.417	0.586	-0.156		
CSR 7	0.012	0.000	0.002			0.001	0.018
	0.907	-0.427	1.409			1.134	
CSR 8	0.010	0.000	0.002	0.007	-0.006	0.001	0.051
	0.659	-0.471	1.490	0.524	-0.213	1.281	

5.4 Fama-French Augmented by a Momentum Factor

As an additional four-factor model, we test Fama-French three-factor model augmented by a widely used factor, momentum, to see whether there is another model performing better than the Fama-French augmented by illiquidity model. The previous four-factor model cannot explain book-to-market effect when scaled with business cycle predictor.

The results presented in Table 5.4 point out a similar scenario observed in the previous four-factor model. The impact of book-to-market on expected returns stay unexplained when the Fama-French augmented by momentum model is scaled only with business cycle predictor. Scaling with size and book-to-market ratio improves the conditional model performance but the static version still cannot provide empirical evidence for the book-to-market effect on average stock returns.

5.5 Fama-French Augmented by Momentum and Illiquidity Factors

Having found the evidence of substantial explanatory power of two four-factor models, we also evaluate the pricing ability of five-factor model which is formed by including illiquidity and momentum at the same time. In Table 5.5, the results for the cross-sectional regression of five factor model are reported. Fama-Macbeth coefficient estimates of the static version of this model are parallel to the static versions of other four models. The coefficient on book-to-market is still significant at a 5% level so we conclude that none of the static versions of these five models is able to explain value premium.

In order to see whether time-varying betas can help to eliminate the predictive power of firm attribute, book-to-market ratio, we test the performance of conditional versions of this five-factor model. Panel 2 of Table 5.5 indicates that scaling beta with size and book-to market ratio leads improvement in the model. Insignificant loadings on all variables mean that five-factor model with this specification can capture the explanatory power of all firm attributes. Nevertheless, when beta is specified as a linear function of business cycle predictor, model performance is not as god as before and is unable to explain the impact of book-to-market on the cross-section of expected returns. Additionally, the last specification that allows beta to vary with size, book-to-market ratio and business cycle predictor produces totally insignificant results. Furthermore, comparing the $\bar{R}^2$

Table 5.4: Fama-Macbeth estimates in FF plus momentum

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 1: $\beta_{kit-1} = \delta_{ki1}$							
CSR 0	0.003						0.000
	1.688						
CSR 1	0.043	-0.002					0.005
	3.762	-3.611					
CSR 2	0.007		0.007				0.006
	3.491		4.462				
CSR 3	0.000			-0.013	-0.067		0.030
	-0.056			-0.899	-2.002		
CSR 4	0.006					0.001	0.009
	2.067					1.727	
CSR 5	0.025	-0.001	0.006				0.011
	2.127	-1.617	3.563				
CSR 6	0.011	0.000	0.005	-0.013	-0.043		0.040
	0.884	-0.629	3.218	-0.904	-1.323		
CSR 7	0.017	-0.001	0.006			0.001	0.022
	1.170	-0.566	3.711			1.079	
CSR 8	0.005	0.000	0.005	-0.013	-0.045	0.001	0.050
	0.308	-0.014	3.245	-0.887	-1.346	1.181	
Panel 2: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki3}Size_{it-1} + \delta_{ki5}BM_{it-1}$							
CSR 0	0.004						0.000
	2.057						
CSR 1	0.037	-0.002					0.005
	3.337	-3.147					
CSR 2	0.006		0.004				0.005
	3.070		2.770				
CSR 3	-0.001			-0.009	-0.024		0.026
	-0.374			-0.693	-0.834		
CSR 4	0.006					0.001	0.009
	2.542					1.993	
CSR 5	0.029	-0.001	0.003				0.010
	2.502	-2.113	1.706				
CSR 6	0.015	-0.001	0.002	-0.009	-0.007		0.036
	1.171	-1.182	1.355	-0.696	-0.255		
CSR 7	0.023	-0.001	0.003			0.001	0.020
	1.662	-1.145	1.743			1.131	
CSR 8	0.007	0.000	0.002	-0.009	-0.010	0.001	0.046
	0.489	-0.394	1.416	-0.692	-0.335	1.443	

Table 5.4 (Continued)

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 3: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$							
CSR 0	0.003						0.000
	1.540						
CSR 1	0.033	-0.002					0.005
	3.053	-2.880					
CSR 2	0.006		0.006				0.007
	3.060		3.958				
CSR 3	-0.001			-0.005	-0.053		0.031
	-0.400			-0.332	-1.711		
CSR 4	0.005					0.001	0.009
	1.862					1.293	
CSR 5	0.016	-0.001	0.005				0.011
	1.486	-0.979	3.258				
CSR 6	0.007	0.000	0.005	-0.004	-0.033		0.041
	0.648	-0.559	2.991	-0.307	-1.067		
CSR 7	0.011	0.000	0.006			0.001	0.022
	0.772	-0.234	3.344			0.912	
CSR 8	0.002	0.000	0.005	-0.004	-0.033	0.001	0.052
	0.148	0.011	3.016	-0.290	-1.054	1.064	
Panel 4: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$							
CSR 0	0.002						0.000
	1.426						
CSR 1	0.020	-0.001					0.004
	2.096	-1.927					
CSR 2	0.004		0.003				0.005
	2.178		2.130				
CSR 3	-0.003			-0.004	-0.016		0.030
	-0.964			-0.286	-0.612		
CSR 4	0.004					0.001	0.009
	1.936					1.400	
CSR 5	0.014	-0.001	0.002				0.009
	1.410	-1.098	1.502				
CSR 6	0.009	-0.001	0.002	-0.005	-0.003		0.040
	0.819	-1.010	1.234	-0.355	-0.114		
CSR 7	0.009	0.000	0.002			0.001	0.020
	0.734	-0.334	1.535			1.070	
CSR 8	0.002	0.000	0.002	-0.005	-0.005	0.001	0.051
	0.112	-0.157	1.358	-0.366	-0.167	1.278	

Table 5.5: Fama-Macbeth estimates in the FF plus momentum and illiquidity

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 1: $\beta_{kit-1} = \delta_{ki1}$							
CSR 0	0.005						0.000
	2.937						
CSR 1	0.039	-0.002					0.005
	3.500	-3.247					
CSR 2	0.008		0.007				0.006
	4.262		4.139				
CSR 3	0.001			-0.014	-0.060		0.029
	0.418			-1.008	-1.793		
CSR 4	0.007					0.001	0.008
	3.125					1.765	
CSR 5	0.022	-0.001	0.006				0.011
	1.904	-1.278	3.349				
CSR 6	0.010	0.000	0.005	-0.015	-0.039		0.039
	0.837	-0.485	2.932	-1.009	-1.176		
CSR 7	0.012	0.000	0.006			0.001	0.020
	0.876	-0.166	3.532			1.325	
CSR 8	0.001	0.000	0.005	-0.014	-0.040	0.001	0.048
	0.093	0.292	3.030	-0.995	-1.194	1.493	
Panel 2: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki3} Size_{it-1} + \delta_{ki5} BM_{it-1}$							
CSR 0	0.005						0.000
	3.145						
CSR 1	0.034	-0.002					0.005
	3.116	-2.845					
CSR 2	0.007		0.003				0.006
	3.547		2.348				
CSR 3	0.001			-0.008	-0.013		0.026
	0.204			-0.612	-0.454		
CSR 4	0.007					0.001	0.008
	3.552					1.800	
CSR 5	0.027	-0.001	0.002				0.010
	2.399	-1.943	1.379				
CSR 6	0.018	-0.001	0.002	-0.008	0.001		0.036
	1.387	-1.318	1.010	-0.632	0.029		
CSR 7	0.024	-0.001	0.002			0.001	0.019
	1.790	-1.243	1.289			0.962	
CSR 8	0.012	-0.001	0.002	-0.008	-0.001	0.001	0.045
	0.831	-0.691	0.984	-0.645	-0.023	1.269	

Table 5.5 (Continued)

	Intercept	Size	B/M	Past 1 month	Past 6 months	Illiquidity	R-squared
Panel 3: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1}$							
CSR 0	0.004						0.000
	2.836						
CSR 1	0.028	-0.001					0.004
	2.716	-2.391					
CSR 2	0.007		0.005				0.006
	3.941		3.549				
CSR 3	0.001			-0.005	-0.048		0.031
	0.245			-0.371	-1.517		
CSR 4	0.006					0.001	0.008
	2.972					1.377	
CSR 5	0.014	0.000	0.005				0.011
	1.238	-0.587	2.982				
CSR 6	0.008	0.000	0.004	-0.005	-0.030		0.041
	0.698	-0.447	2.702	-0.337	-0.953		
CSR 7	0.005	0.000	0.005			0.001	0.020
	0.378	0.292	3.129			1.249	
CSR 8	-0.001	0.000	0.005	-0.005	-0.030	0.001	0.050
	-0.039	0.337	2.823	-0.341	-0.961	1.416	
Panel 4: $\beta_{kit-1} = \delta_{ki1} + \delta_{ki2} z_{t-1} + \delta_{ki3} Size_{it-1} + \delta_{ki4} z_{t-1} Size_{it-1} + \delta_{ki5} BM_{it-1} + \delta_{ki6} z_{t-1} BM_{it-1}$							
CSR 0	0.005						0.000
	3.520						
CSR 1	0.016	-0.001					0.004
	1.690	-1.264					
CSR 2	0.006		0.002				0.005
	3.720		1.945				
CSR 3	0.001			0.001	-0.006		0.030
	0.212			0.104	-0.220		
CSR 4	0.006					0.000	0.008
	3.505					0.913	
CSR 5	0.010	0.000	0.002				0.009
	1.031	-0.468	1.600				
CSR 6	0.008	0.000	0.002	0.000	0.006		0.040
	0.755	-0.661	1.568	0.038	0.237		
CSR 7	0.009	0.000	0.002			0.000	0.018
	0.796	-0.255	1.404			0.702	
CSR 8	0.006	0.000	0.002	0.000	0.006	0.001	0.050
	0.431	-0.291	1.494	0.001	0.207	0.864	

values in unconditional and conditional versions of five models, the lowest $\bar{R}^2$ is obtained in the corresponding versions of five-factor model.

Chapter 6

CONCLUSION

In this paper, we investigate the three conditional and one unconditional specifications of five asset pricing models in order to find evidence for the well-known cross-sectional anomalies in Istanbul Stock Exchange. Extending the methodology in Avramov and Chordia (2006) we examine whether firm specific characteristics which are size, book-to-market ratio, past 1 month return, past 6 months return and illiquidity have an explanatory power for the cross-section of returns.

The empirical evidence shows that multi-factor model perform better than single factor models. Moreover, adding a new factor to Fama-French three factor model improve the pricing ability so four and five-factor models mitigate the impact of firm attributes on average returns. On the other hand, three conditioning specifications are applied to these five models and it is easily observed that time-varying betas make huge contribution to the model. Another documented point of this study is that conditioning only on business cycle predictor does not lead to improvement in model while conditioning on size and book-to-market ratio does. Thus, with additional factors and time-varying betas our models are able to capture the impact of all firm specific characteristics. In sum, this comprehensive, conclusive work offers a wide range of empirical evidence for cross-sectional anomalies of ISE and sheds light to the future studies on one of leading emerging markets.

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