DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF BUSINESS ADMINISTRATION
BUSINESS ADMINISTRATION PROGRAM
DOCTORAL THESIS
Doctor of Philosophy (PhD)

FACTOR MODELS AND MARKET ANOMALIES - EVIDENCE FROM BORSA İSTANBUL

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İZMİR-2018

DOCTORAL THESIS
APPROVAL PAGE

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ABSTRACT

Doctoral Thesis

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Factor Models and Market Anomalies - Evidence from Borsa İstanbul

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In this thesis, we examine the performances of traditional and recent factor models of asset pricing such as Capital Asset Pricing Model (CAPM) of Sharpe (1964), three- and five-factor models of Fama and French (1993 and 2015) and q-factor model of Hou, Xue and Zhang (2016) against market anomalies such as size, value, beta, debt-to-equity, profitability, accruals, corporate investment and momentum for a developing market from July 2006 to December 2015.

For the first time in literature, we test the performance of the five-factor model that is augmented with a cash-based operational profitability based factor, a profitability measure which is completely free from accounting accruals. Recently added profitability and investment factors are motivated from the Dividend Discount Model and these variables are expected to proxy dividends under clean surplus assumption. However, researchers test the performance of the model by using accrual based profitability factors. Consistent with the motivation behind the model, we test the five-factor model with a cash-based profitability factor.

Initially, we implement univariate portfolio analysis to examine the relationship between the anomaly variables and expected stock returns. Our portfolio analysis reveals positive monthly (risk adjusted) premiums ranging from 0.17% (0.06) to 1.69% (1.65) for zero-investment portfolio strategies. However, due to high volatility of stock returns only value and beta effects are statistically

significant. Specifically, the relationship between average stock returns and profitability and average stock returns and corporate investment variables found as weak.

We then investigate the pricing performance of the models. Results reveal that the main problem for these models are their failure to explain the pricing behavior on a portfolio of value stocks whose returns behave like those of small and unprofitable firms that invest aggressively. Additionally, consistent with the findings of the portfolio analysis, recently added profitability and investment factors improve neither the pricing nor the economic performances of the three-factor model. We supplement this finding with portfolio spanning tests and factor optimization. Therefore, even with a cash-based profitability factor, we can conclude that the clean surplus relationship cannot represent dividends and fails to explain common stocks' pricing behavior for an emerging market. The Q-theory of investment fails as well.

Keywords: Factor Models, Asset Pricing, Market Anomalies, Portfolio Analysis, Borsa İstanbul

ÖZET

Doktora Tezi

Faktör Modelleri ve Market Anomalileri - Borsa İstanbul'dan Kanıtlar

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Bu tezde, Sharpe' (1964) ün Sermaye Varlık Fiyatlama Modeli (CAPM), Fama ve French' (1993 ve 2015) in üç ve beş faktörlü modelleri ve Hou, Xue ve Zhang' (2016) nın q-faktör modelinin performansları, büyüklük, değer, beta, borç-öz sermaye, karlılık, tahakkuk, kurumsal yatırım ve momentum gibi piyasa anomalileri üzerinde, Temmuz 2006 ile Aralık 2015 arasında Borsa İstanbul'da işlem gören hisseler için incelenmektedir.

Literatürde ilk kez, beş faktörlü modelin performansı nakit bazlı operasyonel karlılık faktörü, muhasebe tahakkukların dan tamamen arındırılmış bir karlılık ölçütü, kullanılarak test edilmektedir. Son dönemde önerilen karlılık ve yatırım faktörleri temettü indirim modelinden etkilenmektedir ve bu değişkenlerin temiz öz kaynaklar varsayımı altında temettüleri tahmin etmeleri beklenmektedir. Fakat araştırmacılar modelin performansını tahakkuk bazlı karlılık faktörleri kullanarak test etmektedirler. Bu tezde, modelin arkasındaki motivasyon ile uyumlu olarak, beş-faktörlü model nakit bazlı bir karlılık faktörü kullanılarak test edilmiştir.

İlk olarak, fiyatlandırma anomalileri değişkenleri ile beklenen hisse senedi getirileri arasındaki ilişkiyi incelemek için tek değişkenli portföy analizi uygulanmıştır. Portföy analizlerinden elde edilen sonuçlar sıfır-yatırım portföy stratejileri için 0.17% (0.06) ile 1.69% (1.65) arasında değişkenlik gösteren pozitif aylık (riske uyarlanmış) primler ortaya koymaktadır. Fakat, hisse getirilerinin

yüksek oynaklığı nedeniyle yalnızca değer ve beta etkileri istatistiksel olarak anlamlı bulunmuştur. Özellikle, ortalama hisse getirileri ve karlılık ve ortalama hisse getirileri ve kurumsal yatırım değişkenleri arasındaki ilişki zayıf bulunmuştur.

Daha sonra model fiyatlama performansları kontrol edilmiştir. Sonuçlara göre test edilen modellerin genel sorununun agresif yatırım yapan, küçük ve karsız değer hisselerinden oluşan portföyün getirilerini açıklayamaması olduğu gözlemlendi. Ek olarak, portföy analizlerinin sonuçları ile tutarlı bir şekilde, kısa süre önce eklenen karlılık ve yatırım faktörlerinin, model fiyatlama performansını geliştiremediği görüldü. Bu bulgu, model faktör optimizasyonu ile de desteklenmiştir. Bu nedenle, nakit-bazlı bir karlılık faktörü ile dahi, gelişmekte olan bir piyasa için, temiz öz kaynaklar yaklaşımının temettüleri temsil edemediği, dolayısıyla hisse senedi fiyat davranışlarını açıklamada başarısız olduğu sonucuna varılmıştır. Bu bağlamda, yatırım bazlı q-teorisi ‘de başarısız bulunmuştur.

Anahtar Kelimeler: Faktör Modelleri, Varlık Fiyatlaması, Pazar Anomalileri, Portföy Analizi, Borsa İstanbul

FACTOR MODELS AND MARKET ANOMALIES - EVIDENCE FROM BORSA İSTANBUL

CONTENTS

ABBREVIATION

AG	Asset Growth
AG1	Asset Growth 1
AG2	Asset Growth 2
AMEX	American Stock Exchange
ARs	Accounting Accruals
B/M	Book-to-Market Equity
BIST	Borsa İstanbul
CAL	Capital allocation line
CAPM	Capital Asset Pricing Model
CBOP	Cash-Based Operating Profitability
CMA	Conservative Minus Aggressive
D/E	Debt-to-Equity
DDM	Dividend Discount Model
$E(r_i)$	Expected Return on Stocks i
E-R	Expected Return
EU	European Union
E-W	Equally-weighted
FF3M	Fama and French (1993) Three-factor Model
FF5M	Fama and French (2015) Five-factor Model
FM	Fama and MacBeth
GP	Gross Profits
GRS	Gibbons, Ross and Shanken
HML	High Minus Low
I-CAPM	Intertemporal Capital Asset Pricing Model
IG	Investment Growth
LHS	Left-hand Side
ME	Market Value of Equity
NYSE	New York Stock Exchange

OP	Operating Profitability
PPE	Plant, Property and Equipment
$r_m - r_f$	Excess Return on Market Portfolio
RMW	Robust Minus Weak
ROA	Return on Assets
ROE	Return on Equity
SD	Standard Deviation
SMB	Small Minus Big
SML	Security Market Line
TL	Turkish Liras
t-stat	t-stat.
U.S.	United States
U.K.	United Kingdom
USD	United States Dollars
V-W	Value-weighted

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INTRODUCTION

The pricing of risky assets is one of the most challenging topics in the modern finance research. It is complex since common stock prices vary unpredictably depending on the information flow, both related with the future of the firm and environment in which it operates. The problem is that, it is almost impossible to estimate the frequency and *materiality* of this information. Due to uncertain nature of the information, we can call it *risk*. The forward-looking estimates are *pseudo-based*. The only source of information, risk, is historical records and academics continuously examine the past to reveal measurable patterns which incorporate a *material* information.

Since the beginning of the modern portfolio theory, in 1950s, there has been an endless venture toward identifying the simplest pricing equation which incorporate the effects of *risk* on asset prices and able to fully describe them. However, more than half-century of experience reveals that, this task is very hard. On one hand, academics continuously search for predictable patterns in past stock returns. And, they reveal plenty of pricing effects in the last half-century. On the other hand, they update the pricing equation to fully describe these effects. Despite all, do we now have an equation that provides us with a complete understanding of stock price movements? The answer is an absolute no. Yet, according to Fama and French (hereafter FF) (2017: 18) there always a value in searching an equation that provides the best. Our effort in this thesis is in the same direction.

It is essentially the Capital Asset Pricing Model (hereafter CAPM) of Sharpe (1964) which started this endless quest. The CAPM speculates a linear relationship between common stock returns and market portfolio returns. In other words, according to the theory, the market portfolio is mean-variance efficient and incorporate entire news, *risk*, relevant to asset pricing and it is suffice alone to describe them. However, empirical evidence from both developed and developing markets by FF (1992 and 2016) and Rouwenhorst (1999) shows that this relationship is flat. Additionally, average returns on the U.S. market common stocks are strongly related to firm specific variables. Banz (1981) document a negative relationship between market capitalization (shares outstanding times price, hereafter ME) and returns, Rosenberg, Reid and Lanstein (1985) document a positive relationship between book-to-market equity (hereafter B/M) and returns, Novy-Marx, (2013) document a positive relationship between profitability and returns, Cooper, Gulen and Schill (2008) document a negative relationship between corporate investment and returns, Jegadeesh and Titman (1993) document the momentum effect and Sloan (1996) document a negative relationship between accounting accruals (hereafter ARs) and returns. The empirical evidence from developed[1] and developing[2] international markets is similar: CAPM cannot explain these relationships.

Because of the failure of CAPM, FF (1993) offer a three-factor model (hereafter FF3M) that augments CAPM with size (SMB) and value (HML) factors. The motivation behind these factors is empirical findings pointing relationships between ME and average returns and B/M and average returns. FF3M performs better than CAPM in explaining returns on portfolios sorted by size and B/M. However, empirical evidence from Ball et al. (2016), Cooper et al. (2008), Hou, Xue, and Zang (2016), Novy-Marx (2013) and Vo (2015) reveals that FF3M cannot fully explain stock returns related to momentum, profitability, ARs and corporate investment variables. Recently, FF (2015) augmented FF3M with two additional factors, namely, RMW (robust profit tracking portfolio) and CMA (conservative corporate investment tracking portfolio). They argue that their new model provides a better description of average returns since these new factors are neutral suggestions of the Dividend Discount Model (DDM) of Miller and Modigliani (1961). DDM predicts a positive relationship between the market value of securities and expected future dividends discounted with the internal rate of return on expected dividends. Formally,

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(D_{t+\tau})}{(1+r)^{\tau}} \qquad \text{(eq.1)}$$

[1] See, for instance, Amman, Sandro and Oesh (2012), Chan, Hamao and Lakonishok (1991), Chan and Zhang (1998), FF (2017), Heston, Rouwenhorst and Wessel (1999) and Novy-Marx (2013).
[2] See, for instance, Cakici, Fabozzi and Tan (2013), FF (1998 and 2012), Guo et al. (2017), Özkan and Kayali (2015), Rouwenhorst (1998 and 1999), and Zaremba and Czapkiewicz (2017).

where M_t is the market value of security of stock at time t, D_t is expected dividends at period t + Ꚍ, and r is the internal rate of return on expected dividends. According to eq.1, if *r* held constant, M_t increases with expected dividends.

Under the clean surplus accounting assumption, dividends can be represented by the expected future earnings minus the expected yearly change in the book value of equity. Hence, we can reorganize *DDM* as follows,

$$M_t = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau})}{(1+r)^{\tau}} \qquad \text{(eq.2)}$$

where M_t is the market value of a security at time t, Y_t is the expected earnings at time t + Ꚍ, *d*B is expected change in book equity from t-1 to t ($B_t - B_{t-1}$), and r is the internal rate of return. Deflating both sides of the equation by the time *t* book value of equity provides

$$\frac{M_t}{B_t} = \sum_{\tau=1}^{\infty} \frac{E(Y_{t+\tau} - dB_{t+\tau}) \,/\, (1+r)^{\tau}}{B_t} \qquad \text{(eq.3)}$$

If everything other than M_t and *r* is kept constant, equation 3 implies that the expected returns (hereafter E-Rs) increases with a lower current M_t, and/or with a higher current B/M ratio. In a similar manner, if only *r* can vary, and others are kept constant, higher expected earnings imply higher M_t and hence, higher E-Rs. Conversely, if *r* kept constant, higher expected corporate investment implies lower E-Rs since there will be less cash flow available to the shareholders.

Accordingly, the five-factor model (hereafter FF5M) of FF (2015) speculates that expected excess return on any asset, *i*, can be given by its exposure to the five factors: excess return on market portfolio ($r_m - r_f$), SMB, HML, RMW, and CMA. Therefore, in the time series regressions,

$$r_i - r_f = \alpha_i + b_i\left(r_m - r_f\right) + s_i SMB + h_i HML + r_i RMW + c_i CMA + e_{it} \qquad \text{(eq.4)}$$

where, $r_m - r_f$, SMB, HML, RMW and CMA are expected premiums and b_i, s_i, h_i, r_i, and c_i, are factor loadings. The final term is residuals with an expected mean of zero and the first term is the intercept (α). Leaning towards Huberman and Kandel (1987), if these factors can fully describe the average returns, then α_i should be zero in the time-series regressions for any set of combinations of left-hand side (hereafter LHS) assets. A time-series methodology enables us to test these predictions.

Borsa İstanbul (BIST) is a good place to test these predictions for several reasons. First, dividends in equation 1 represent residual cash flows to the claim holders that remain from cash profits. Therefore, the use of a cash-based profitability measure for FF5M is theoretically appropriate. However, to the best of our knowledge, FF5M has never been augmented with a cash-based operational profitability (hereafter CBOP) factor that is completely free from ARs. ARs are adjustments by accountants to transform cash profits into accounting earnings (Ball et al., 2016: 30), hence, they do not represent economic profitability and are not relevant to dividends. Therefore, the use of a cash-based profitability factor in a test of FF5M is in line with the theory underlying the model. BIST provides a nice setting for this test since, developing markets structured like BIST can give rise to aggressive use of ARs[3]. Therefore, BIST can reveal the true potential of the cash-based profitability factor.

Second, BIST provide a nice ground for out-of-sample setting to reveal new evidence since most of the anomalies that are pronounced in developed markets have never been investigated for the BIST. Importantly, these anomalies may not exist in developing regions. For instance, Guo et al. (2017) find no evidence of investment anomaly in China. Cakici et al. (2013) find no evidence of momentum anomaly in Eastern Europe. And, FF (1998) find no evidence of value anomaly in several emerging markets namely Argentina, Jordan and Colombia.

Third, pricing anomalies expected to intensify in emerging markets with lower liquidity and higher transaction costs. According to Zaremba and Czapkiewicz (2017: 2) the illiquidity of stocks and relatively higher transaction costs can elevate abnormal returns on anomalies.

Finally, we are still unaware of the pricing patterns in BIST in relation to the speculations of equation 3. It is important to reveal whether the predictions of a rational pricing theory apply in an emerging market. Importantly, we are still unaware of the

[3] See Yurtoglu (2000) for a nice study on ownership structure of BIST companies.

performance of more recent factor models for the pricing of common stocks on BIST. The new model is motivated from the rational pricing theory. Therefore, it has the potential to provide a better description of average stock returns.

Accordingly, this thesis tests the predictions of equation 3 and examines the performances of CAPM, FF3M, the q-factor model and FF5M against pricing anomalies such as size, B/M, beta (hereafter β), debt-to-equity (hereafter D/E), profitability, ARs, investment and momentum, for the common stocks listed on BIST from July 2006 to December 2016. The motivation behind the choice of these models and anomalies is CAPM theory, equation 3, q-theory of investment and prominent empirical evidence.

To analyze the relationship between the fundamental variables and E-Rs, we prefer portfolio sorts over cross-sectional regression. The reason for this choice is the characteristics of our data and aim of the thesis (for details see *Section 3.3.1*). We examine the relationship between E-Rs and fifteen different variables, including five profitability variables, both earnings-based and cash-based, three corporate investment variables and two prior return measures. We evaluate both the value-weighted (V-W) and equally-weighted (E-W) portfolio investment strategies for these variables. In the calculation of portfolio and factor breakpoints, we use market and big stocks; hence, our results are largely free from the tiny stock effect. We check the robustness of our factors with other factors which uses sample breakpoints.

We then turn our attention to asset pricing tests. As per FF (1993), we evaluate the model performances by using a time-series regression methodology. In addition, we test the mean-variance efficiency of factors by using Gibbons, Ross and Shanken (1989) (GRS) test. To measure the economic significance of models, we calculate several statistics which measures the alpha (α) dispersion of models. Finally, we supplement our results by using the spanning regression and factor optimization.

We can describe our main finding as follows; all the models fail against the B/M effect; hence, they cannot provide complete description of average returns. The inclusion of factors SMB and HML to the CAPM equation is appropriate since the returns on a zero-investment portfolio of small stocks and the returns on a zero-investment portfolio of value stocks do not significantly expose to β. Additionally, small and value stocks are riskier with high debt and low profitability, respectively. In contrast, the relationships between average returns and profitability and average returns and corporate investment variables is too weak and insignificant. Therefore, the factors of RMW and CMA are unnecessary in BIST. Analogously, the test performance statistics, spanning regressions and factor optimization justify this conclusion. The RMW and CMA never improve the performance of FF3M, whereas, SMB and HML improve the performance of the CAPM. Finally, a q-factor model, which drops factor HML, always underperforms FF3M and FF5M. These findings indicate that the clean surplus relationship of FF (2006) and q-theory of investment cannot explain the common stock pricing behavior in an emerging market.

We can list the important contributions of this thesis as follows; first, it augments a cash-based profitability factor with FF5M. To the best of our knowledge, this is the first study in the finance literature that adopts a CBOP factor to test the clean surplus relationship. In their study, FF (2015) use earnings before extraordinary items as a proxy for the expected profitability effect. However, earnings include ARs that are not relevant to dividends since they represent accounting numbers and not cash earnings. This thesis provides the very first evidence concerning the performance of FF5M with a cash-based profitability factor.

Second, this thesis is the first to test the speculations of the rational pricing equation of FF (2006), namely, the relationships between E-Rs and cash profitability and E-Rs and corporate investment for the securities listed on BIST. Unfortunately, results demonstrate that the relationship between E-Rs and these variables are not so pronounced and therefore contradict those of FF (2006 and 2015). Accordingly, the results show that the RMW and CMA factors cannot improve the performance of FF3M. From an economic point of view, the thesis suggests the irrelevancy of these factors for BIST stocks. Theoretically, the clean surplus relationship does not hold for an emerging market. However, the results are silent regarding an alternative theory.

Finally, this thesis documents eight different investment strategies that yield economically large positive monthly premiums. These premiums are even larger than those of developed markets and are comparable to those of developing markets. Therefore, suppliers of capital and professional portfolio managers will be better off including stocks in their portfolio with high β, low ME, high B/M, high D/E, high profits, low ARs, low investment and momentum properties. Whereas, from a statistical point of view, only the B/M and β can significantly predict E-Rs. One of the reasons behind the insignificant premiums is their highly volatile returns, which is a common finding in emerging markets (FF, 1998: 1993).

This thesis is organized as follows; Following the introduction, Chapter 1 provides a theoretical background. Chapter 2 provides a detailed literature survey. Chapter 3 describes the sample and methodology. Chapter 4 reports findings. Chapter 5 provides a discussion. Final section presents the conclusions.

CHAPTER ONE
THEORETICAL BACKGROUND

Selection of the risky assets and construction of the actively managed portfolios have always been in the center of investment economics. Chapter one provides details about the developments in the security selection, asset pricing and portfolio construction literature of financial economics.

1.1. THE MARKOWITZ APPROACH TO SECURITY SELECTION

At first, construction of risky portfolios was dependent on the E-R criterion. Investors adopting E-R criterion was giving priority to the allocation of their wealth into stocks with the highest E-R. However, with a groundbreaking study Markowitz (1952) show that the E-R criterion is not efficient. According to him portfolios should be constructed under the principle of “right diversification” (Markowitz, 1952: 89) by focusing both on the returns and the variance of returns. The new way is called the E-R and the variance of returns criterion and rather holds that the primary focus should be on the co-variation between security returns when picking up securities for an investment portfolio.

To understand which criterion is better, we should focus on to the portfolio characteristics, such as: E-Rs and variance. These characteristics derive from investors’ adjustment on the proportions of wealth invested into securities and the collective interaction of those securities within a portfolio. In this context, E-R on a portfolio is the simple weighted summation of E-R on each security; hence, determined by the proportions of wealth invested (w) into each security. Formally,

$$E(r_p) = \sum_i w_i E(r_i) \qquad \text{(eq.5)}$$

The case of variance is more complex. Markowitz (1952: 80) argues that the variance should be obtained by the co-variation matrix, which is constructed from the interaction of returns on each security in a portfolio. He basis this foundation on the tendency of co-movement of stock returns because of unavoidable changes in the underlying economic forces. Accordingly, co-variance between returns of two securities (i.e. *i* and *j*) should be considered when allocating wealth into different stocks because the co-variance is what determines portfolio's total variance. This can be understood by the way variance is calculated. To illustrate, in the case of two stocks, variance can be derived as the multiplication of fractions, w, invested into stocks i and j, and the co-variance coefficient between their returns[4],

$$\sigma_p^2 = \sum_i \sum_j w_i \, w_j Cov\,(r_i\,, r_j) \qquad \text{(eq.6)}$$

The co-variance, on the other hand, is the deviation of E-Rs of security *i* from its expected mean times the deviation of E-Rs of security *j* from its expected mean.

$$Cov_{i,j} = E\{[r_i - E(r_i)][r_j - E(r_j)]\} \qquad \text{(eq.7)}$$

Arguably, the co-variance is what really matters on portfolio's overall and incremental risks. It has a direct effect on variance through the amount of allocated wealth to a security. Therefore, diversification is fundamental and expected return-variance criterion is superior. Poorly diversified portfolios, in other words portfolios including stocks with highly co-varying returns, can cause the erosion of wealth. In this manner, if possible, investors should search for the lowest co-variance values while meeting the desired level of return expectation.

Consequently, according to Markowitz (1952: 77) portfolio selection includes two stages. Initial stage begins with the security analysis, and the product of this stage is expectations related with future performances. In contrast, stage two begins with relevant expectations, and the product of this stage is the investment portfolio. In stage one, investor form set of beliefs related with the prospects of the securities and then proceeds to the formation of *efficient* portfolios, including these securities with varying weights. The *efficient* portfolios mean that there is no other combination that provide a better risk-return relationship for the desired level of risk, or the desired level of return (Markowitz, 1952). Later, by plotting each portfolios' characteristics on the expected return-SD plane,

[4] This condition for E-R and variance hold under two assumptions; weights should be positive (i.e. short sales are restricted), and add up to one.

investors arrive an arc called the “efficient frontier of risky assets” (Bodie et al., 2014: 222). Having identified all the portfolios with most favorable characteristics for given return or variance constraint, investors can choose among the opportunity set that yields maximum utility satisfaction.

Derivation of this approach simply based on the utility maximization maxim of individual investment behavior. Different combinations of portfolios built on a simple logic, yet heavy work.

1.2. AFTERSHOCKS OF MARKOWITZ, PRECURSORS OF CAPM

The Markowitz’s (1952) approach was a breakthrough for modern portfolio theory. Later Tobin (1958) took the development of portfolio formation process one step forward. Author include a risk-free alternative, cash, into the process. According to him the portfolio formation includes two steps that are independent one another – the *separation theory*. First, investors optimize the composition of their risky portfolios using the Markowitz’s procedure. Second, they determine the amount of wealth which is to be shared among the riskless alternative and risky portfolio. In Tobin’s approach the characteristics of the risky portfolio is constant, investor just decide the extent of exposure to it by the amount of wealth he/she allocates.

In another groundbreaking study, Sharpe (1963) offer a way to simplify the first step, the construction of investment opportunity set. Idea of Markowitz was brilliant. However, it requires enormous number of estimates. For example, to obtain an efficient frontier entire investment universe should be analyzed. Let alone analyzing the entire universe, in the case of only 20 stocks, 20 estimates of E-Rs, 20 estimates of variances of E-Rs, and 190 $[(n^2 - n) / 2)]$ estimates of co-variances is needed. To aid this, Sharpe (1963) offer the corner portfolio terminology. According to author, any portfolio on the efficient frontier can be constructed by focusing only on the two adjacent portfolios. The most brilliant contribution of the diagonal model is, it assumed a common factor that is responsible from the co-variation between securities’ returns. According to Sharpe (1963: 281), this can be a price index.

Arguably, together with Markowitz (1952), the developments by Tobin (1958) and then Sharpe (1963) gives the way to the one of the most brilliant foundations of financial economics by Sharpe (1964) and Lintner (1965), the CAPM.

1.3. THE CAPM

Methodology of Tobin (1958) and Markowitz (1958) was built on a common intuition; given the prices of risky assets investors forms *unique* probability distributions related with the E-Rs. Whereas, Sharpe (1964) and successors Lintner (1965) and Mossin (1966) show that when investors hold *homogeneous* expectations related with future prospect of assets, they form joint probabilistic distributions related with the E-Rs. Hence, each arrive a common optimal risky portfolio. The fraction of wealth to be invested, *w*, in any asset within these optimal portfolios will be equivalent to the market price of that firm. This is because, the market price equals to the fundamental price under homogeneity of expectations assumption. Meaning that, the fraction of investment in any risky asset will be the same for every mean-variance optimizing agent. Accordingly, optimized individual homogeneous portfolios will accumulate to a comprehensive portfolio, the *market portfolio*. The market portfolio is the most *efficient* portfolio based on its risk-return characteristics and information content.

Including the riskless alternative to the process, lending or borrowing at the same rate that is for everyone, the tangency of capital allocation line (CAL - a straight line that connects risk free asset and the efficient risky portfolio on the mean-standard deviation plane) to the "investment opportunity curve" (Sharpe, 1964: 429) point out the most efficient portfolio, the market portfolio. The tangency point yield to the market portfolio because of the accumulation property. The demand-price mechanism ensures that all the assets in an economy will take place in this portfolio at some point in time. Therefore, the market portfolio is informationally efficient, providing the best risk-return tradeoff, alternatively the best Sharpe Ratio. In this manner, investors cannot beat the market in CAPM theory. Therefore, rational investors are expected to allocate part of their wealth into the market portfolio as the best risky alternative and part of it into the riskless alternative. Of course, the investment pattern to this linear combination is based on the personal utility maximization. According to Sharpe (1964), this equilibrium condition enables the valuation of financial assets by leading to a "simple linear relationship between the expected return and the standard deviation of return for efficient combination" (Sharpe, 1964: 436).

Investors holding market portfolio should not concern about the total risk of any asset because of the benefits of diversification (Markowitz, 1952). The efficient optimization of market portfolio diversifies away the firm specific risk factors, since this risk source is random and uncorrelated among firms. What remains back called the "systematic risk" (Sharpe, 1964: 339). According to Sharpe (1964), the systematic factor is what underlies the co-variation among security returns and it is the only relevant risk to consider when holding efficient portfolios and dealing the pricing of other assets. The reason is simple, sensitivity of asset returns to the movements in the systematic factor (i.e. market portfolio), should be the only relevant factor that determines the risk, expected return and demand towards a stock (under the assumption of fixed supply of risky assets). Accordingly, Sharpe (1964) and Lintner (1965) show that,

$$E(r_i) - r_f = r_f + \beta_i \left[E(r_m) - r_f\right] \qquad \text{(eq.8)}$$

where r_i is the returns on stock *i,* r_f is the returns on risk-free asset, r_m is the returns on market portfolio and β is the slope. The CAPM equation states that the expected excess returns (expected return over the risk-free rate) on any asset is linearly related to expected market risk premium (market return over the risk-free rate) with intercept at the risk-free interest rate. This linear relationship is measured with the slope of the equation, the beta (β). The β coefficient measures the sensitivity of security returns to the movements in the systematic factor (i.e. market premium) and derived by the ratio of security's co-variance with the market to the market variance;

$$\beta_i = \frac{Cov\ (R_i, R_m)}{Var\ (R_m)} \qquad \text{(eq.9)}$$

Accumulation property forces market β to sum up to 1. The plane plotting E-Rs on the market portfolio against its beta ($\beta_m = 1$) referred to as Security Market Line (SML). All the stocks, based on their expected return-β relationship, should lie on the SML under

CAPM assumptions. This implies that, investors can increase their expectations on additional return only through bearing additional risk, or in other words, by taking place far right of the CAL gearing toward the market portfolio. This is known as the "price of risk" (Sharpe, 1964: 425). An asset should only provide the commensurate gains based on its β; hence, investors should not be able to beat the market. Market should correct any returns beyond what β suggest. The CAPM theorized the relationship between the E-Rs of financial assets and their risk.

To attain necessary environment for the return-β relationship, several assumptions were established. Following section describe these assumptions and their implications.

1.3.1. Assumptions of the CAPM

The assumptions of CAPM can be investigated under two categories; (i) assumptions dealing with the behavior of the individuals and (ii) assumptions dealing with the structure of the market. Assumptions dealing with the individual behavior can be listed as;

1a. Investors rationally optimize for mean and variance; deals with individual wealth management behavior and how equilibrium prices are attained.

1b. Investment horizon is a single period; to eliminate the possibility of facing additional risks (e.g. interest rate) that will lead investors to hold additional hedging position and diverge from the market portfolio.

1c. Investors hold homogenous expectations; related with E-Rs, standard deviation (hereafter SD) and correlations of given assets; hence, they arrive identical input list and form identical efficient frontiers.

In contrast, assumptions concerning with the structure of market can be listed as;

2a. All the assets are publicly traded, and investors can lend-borrow at the same risk-free rate; to ensure that the mean-variance relationship is not violated by non-traded assets (i.e. privately held businesses and human capital) which represent a substantial part of the economy (Baxter and Jermann, 1997). Additionally, facing different risk-free rate will lead different tangency points (i.e. different optimal risky portfolios).

2b. Entire information is available to the public; to attain consistency of expectations related with the future prospect of firms.

2c. No trading taxes; to face same tax realizations and construct similar optimal portfolios.

2d. No trading costs; to ensure the efficiency of the market portfolio. No costs in CAPM ensures that the investors will engage in portfolio optimization whenever new information arrives.

In a nut shell, implied assumptions lead to a mean-variance efficient portfolio which incorporates the entire fundamental economic information relevant to asset pricing. Therefore, according to Sharpe (1964), Lintner (1965) and Mossin (1966) β should be the only relevant risk to consider when pricing common stocks. The larger the exposure to it, the larger the returns. In theory, the CAPM seems flawless. However, academics define these assumptions as *unrealistic.* In addition, evidence suggest that there is no β effect. And, there can be inefficiencies in the market prices. For example, historical stock patterns incorporate fundamental information that cannot be captured by the β. Following section investigates these challenges, respectively.

1.3.2. Challenges to the Assumptions of the CAPM

CAPM is criticized for holding restrictive assumptions. Black (1972) argue that, limitless positions and lending and borrowing at the same riskless rate is exceptional. Particularly, when borrowing is not allowed, traditional CAPM equation (eq.8) could not be applied. Bodie et al. (2014: 305) emphasize on the challenging nature of short positions[5]. However, according to them, main problem of the CAPM is the trading of all assets, single investment horizon and costless transaction assumptions.

[5] According to Bodie et al. (2014) short positions are restricted in many countries and requires enormous amount of collaterals. Additionally, the supply of shares is limited and shares cannot be borrowed limitlessly.

For instance, trading of all assets assumption ensures that the market portfolio represent the entire risky assets in an economy (Bodie et al., 2014). However, Jagannathan and Wang, (1996) show that stock market represents only a limited portion of risky assets in economies. Jagannathan and Wang (2007) construct a model by replacing market portfolio of CAPM with consumption growth. Their U.S. based consumption growth model perform better than the traditional CAPM from 1954 to 2003. Additionally, Merton (1973) show that the CAPM is intertemporal. When single period assumption has been relaxed, investors demand for hedging towards other risk factors, like future inflation and different future risk-free rate, that could be arise in multiperiod investing. Consistently, Bollersev, Engle and Wolldridge (1988) show that the co-variance matrix is conditional on lagged asset returns, meaning that market β is time varying.

Implied criticisms and others led multiple variations of CAPM[6]. However, main challenge to the theory arises from two important empirical findings; (i) β effect is weak or even non-existent and (ii) variation in stock returns are also related to firm specific factors. These topics are investigated in the following chapter in more detail.

[6] Additional variations of the CAPM not discussed here since they are over the scope of the current discussion. Brief review provided to enable the chronological description of the subject under investigation. Interested readers are advised to survey Amihud and Mandelson (1986), Barberis et al. (2015), Breeden (1979), Fama (1970), Heaton and Lucas (2000), Jahannathan and Wang (1996), Lucas (1978) and Rubinstein (1976).

CHAPTER TWO
LITERATURE REVIEW

Chapter two summarizes findings of the studies that examine the relationship between the firm specific factors and average stock returns. Additionally, it summarizes the performance of the factor models of asset pricing. The firm specific factors those are considered in this thesis is market capitalization (hereafter ME), B/M, market β, D/E ratio, profitability, corporate investment and momentum.

2.1. IS THERE ANY β EFFECT?

The ultimate question is that, "is there any β effect?". As a matter of fact, we are not sure. The validity of CAPM have been examined in many studies. Fama and MacBeth (FM) (1973) justify the linear association between E-Rs and market β from 1926 to 1968. However, most of the empirical findings is against this finding.

Among these studies, Friend and Blume (1970) find that the returns on a portfolio of stocks with higher βs is lower than the returns on a portfolio of stocks with lower βs from 1960 to 1968. The result of the study of Black, Jensen and Scholes (1972) is almost similar. Reinganum (1981a) finds that portfolios consisting of stocks with different level of βs have, statistically speaking, similar average returns in New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). Consistently, FF (1992) argue that "…the relation between market β and average returns is flat" (FF, 1992: 427). Lakonikos and Sharpio (1986), Miller and Scholes (1972) and Reinganum (1981b) obtain similar results[7]. International evidence related with the E-R and β relationship is analogous. Rouwenhorst (1999) fail to document any difference between the returns of

[7] Some argued that the CAPM's validity tests are inappropriate. According to Roll (1977) it is not possible to know the exact composition of the market portfolio and this shortcoming imposes restriction on the empirical examination of the theory. Consistently, according to Roll and Ross (1994) and Kandel and Stambaugh (1995) tests of CAPM is critically dependent on the mean-variance efficiency of the market portfolio, it must be *truly efficient*. Otherwise market β will fail to reflect the mean-variance relationship.

high beta stocks versus low beta stocks for a large sample of non-U.S. developed and developing markets. These results indicate that β has no market price.

Assumptions of CAPM postulate that, (i) market portfolio is mean-variance efficient and incorporate all the information related with the pricing fundamentals; hence, it is alone sufficient in explaining E-Rs and (ii) there is a linear relationship between E-Rs and market β in which additional returns only attained through bearing additional market risk. However, empirical evidence indicates that the CAPM's postulations are problematic. Additionally, Reinganum (1981a) show that the low risk portfolios, measured with βs, extracts positive α values, and *vise-versa*. According to Black et al. (1972), if the assumptions of traditional CAPM equation justify the risk-return relationship, the intercept factor, α, must be statistically indistinguishable from zero for any asset in the time-series regression.

Hypothesis 1: *Contrary to the CAPM, return-β relationship is flat and inadequate.*

The inadequate return-β relationship is not the only problem for the traditional CAPM equation. Arguably, main problem related with the CAPM equation is that, it cannot explain average returns on portfolios that are sorted by various firm specific characteristics. According to Reinganum (1981a), these firm specific effects are referred to as "anomalies" (Reinganum, 1981a: 439) since they are anomalous to the CAPM theory.

In the following part the related studies are presented.

2.2. MARKET CAPITALIZATION AND EXPECTED-RETURNS

Banz (1981) reveal that the stocks of NYSE firms with small market capitalization (market worth of shares outstanding) provide higher returns than their β suggest from 1926 to 1975. According to him, the ME effect, or alternatively, the *size effect* "…has been in existence for at least forty years" (Banz, 1981: 3). Reinganum (1981b) observe the same effect.

Size effect has been investigated by many researchers. Among them, Brown, Kleidon and Marsh (1983) show that the size effect depends on the sampling period. Additionally, Lakonishok and Sharpio (1986), and Jaffe, Keim and Westerfield (1989) show that the return on small ME stocks are higher only in January. In contrast, Keim (1985) finds that the size effect is stronger in January, however, it occurs throughout the year. Similarly, Banz and Breen (1986) justify the size effect for the U.S. market.

Economic explanations emerge to explain this anomalous pattern. According to Roll (1981), the small stocks are usually less traded and illiquidity of the small stocks lead suppressed β estimates and ultimately to the size effect[8]. In contrast, Stoll and Whaley (1983) reveal the important impact of high transaction costs on trading small stocks. According to them costs influence arbitrageurs' position taking ability. However, Reinganum (1982) and James and Edmister (1983) justify the size effect even after the adjustment of the trading infrequency. In contrast, Chan and Chen (1988) show that the size effect may be a product of measurement errors in β since ME and β are highly correlated. However, Jegadeesh (1992) form test portfolios sorted by size and β and reveal that the β cannot account for the size effect. The results of the study of FF (1992) confirms Jegadeesh (1992). Returns on a portfolio consisting low-β small stocks is higher than the returns on a portfolio consisting high-β big stocks from 1962 to 1989 in the U.S. market. According to Brown et al. (1983), part of the size anomaly can be clarified by fundamental factors that researchers omits. Analogously, Chan, Chen and Hsieh (1985) argue that the size variable may be delegating the impact of a more fundamental risk factor, such as the default risk. Considering these implications, Chan and Chen (1991) show that the small firms are usually marginal firms, having higher D/E ratios and lower productive efficiency. Therefore, such firms respond differently to an economic news compared to others.

Empirical evidence show that size variable still maintains its negative relationship with average returns in the U.S. markets (Ball et al., 2015; FF, 2015; Novy-

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[8] Roll (1981) basis his infrequency of trading argument to the works of Scholes and Williams (1977) and Dimson (1979). Authors show that the beta estimates of infrequently traded shares eligible to expose a downward bias, and *vise-versa*.

Marx, 2013). In addition, the size anomaly is robust against β and in existence at least from mid-1920s. Therefore, size variable may be delegating an underlying risk factor that is yet to be observed (FF, 1993). Size effect is the "most prominent" (FF, 1992: 427) pattern that contradicts with traditional pricing equation of Sharpe (1964) and Lintner (1965).

Consequently, β and ME does not represent the same factors underlying the co-variation between security returns (FF, 1992: 450), meaning that ME has a descriptive power over β. Additionally, low ME firms are riskier. Therefore, traditional CAPM equation may be miss-specified; hence, it might be appropriate to use an additional factor that mimics the size investment effect in rational asset pricing equation.

Hypothesis 2a: *Small stocks tend to be distressed with higher debt levels and lower earnings.*

Hypothesis 2b: *The CAPM is miss-specified since ME is negatively related with stock returns.*

2.2.1. Size Effect in Non-U.S. Developed Markets

Many observe the size effect in other developed markets. Heston, Rouwenhorst and Wessel (1999) investigate the relationship between ME and average returns for twelve developed EU markets[9]. They find a relationship between ME and average returns for all the countries, except Italy, from 1980 to 1995. For instance, financing a portfolio consisting of small stocks with a portfolio consisting of big stocks[10] provide average monthly premium of 0.48%, 0.75% and 0.39% in Austria, Spain and the United Kingdom (UK), respectively[11]. In addition, they show that the size effect is persistent in these

[9] Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the U.K.

[10] Cochrane (2000: 19) refers such strategies as "zero-cost portfolio" or "self-financing portfolio". Here trader takes a long position on the portfolio of stocks with high E-Rs and short position on the portfolio of stocks with low E-Rs.

[11] Size strategy used by Heston et al. (1999) represents E-W portfolios formed based on ME medians of the markets, as big (top 50%) and small (bottom 50%). Premiums represent average monthly returns on the portfolios of small minus big stocks. For details survey Heston et al. (1999), page 23, Table 6.

markets throughout the year. Chen and Zhang (1998) observe the same effect for Japan and Hong Kong markets. According to them, monthly premium on a similar investment strategy[12] in Japan and Hong Kong is 0.79% and 3.15%, respectively. Laledakis and Davidson (2001) examine the ME effect for the U.K. market from 1980 to 1996 and they find similar results. In their study, they use ten quintiles and show that the annual premium on the size investment strategy is 1.80%. Chan, Hamao and Lakonishok (1991) observe a similar effect in Tokyo Stock Exchange (TSE) from 1971 to 1988. Finally, FF (2012) examine twenty-three markets from four different regions, namely, Asia Pacific, North America, EU and Japan, for the size effect and document that the portfolios sorted by size provide high returns only in North America[13].

2.2.2. Size Effect in Developing Markets

Rouwenhorst (1999) investigate twenty developing markets[14] from 1982 to 1997 and observe size effect in twelve of them, only three of which were statistically significant. According to him, Argentina is the most profitable place to chase polar deciles size investment strategy from 1982 to 1997. Average monthly premiums on a zero-investment small portfolio is 3.84%. Premiums on the same strategy are 2.23% and 2.39% for Malaysia and Mexico, respectively[15]. The findings of Chen and Zhang (1998) about Malaysia, Thailand, and Taiwan is consistent[16] with that of Rouwenhorst (1999).

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[12] Chan and Zhang (1998) form portfolios based on five market quintiles. For details survey page 506, Table 2 and page 508, Table 3.

[13] For details survey FF (2012), page 461, Table 1.

[14] Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, and Zimbabwe. According to FF (1992 and 1993) high SDs of portfolio returns may responsible from insignificant t-stat. on hedge portfolio premiums.

[15] Size strategy used by author represents three E-W portfolios sorted by ME as large (top 30%), medium (middle 40%) and small (bottom 30%). Size premium represents average returns on small minus large stock portfolios. For details survey Rouwenhorst (1999), page 1447, Table 2.

[16] Authors form portfolios based on five market quintiles. Premiums are monthly. For details survey Chen and Zhang (1998), page 510, Table 4, page 512, Table 5 and page 514 Table 6, respectively.

Recently, Hasan et al. (2015) and Lischewski and Voronkova (2012) justify the size effect in Bangladesh, from 2003 to 2015, and Poland markets, from 1996 to 2009, respectively. De Moor and Sercu (2013) investigate thirty-eight developing and developed markets, including the U.S., from six regions (i.e. North America, Latin America, Japan, non-Japan Asia, Continental and non-continental Europe, Australasia and South Africa) from 1980 to 2009 and reveal that the relationship between size and returns are not linear. Çakici, Fabozzi and Tan (2013) investigate eighteen developing financial markets under three regional classifications such as, Asia, Latin America and Eastern Europe, and they reveal a weak size effect.

2.3. B/M AND EXPECTED-RETURNS

Common stocks with higher book value of equity, dividends, earnings and cash flows relative to their market prices referred to as value stocks (La Porta, 1996). Capaul et al. (1993: 27) defines value investing as "…selecting companies whose securities can be purchased for prices that are low relative to companies' estimated underlying value". Empirical evidence from Basu (1977 and 1983), FF (1992), Keim (1985), Lakonishok, Shleifer and Vishny (1994) and Rosenberg, Reid and Lanstein (1985) suggests that the average risk adjusted returns on value stocks is higher. Therefore, investing strategies that finance a portfolio of value stocks with a portfolio of growth stocks provide positive returns. Arguably, most influential measure of value is the B/M ratio. The B/M can subsume information carried by other value measures (FF, 1992; 441).

Rosenberg et al. (1985) examine the value effect and document an average monthly premium of 0.36% on buying a portfolio of high B/M stocks (i.e. value stocks), and selling a portfolio of low B/M stocks (growth stocks), from 1973 to 1984. According to FF (1992), monthly value premium from 1963 to 1990 is 0.99%. Likewise, FF (1995) observe annual average value premium of 6.95% from 1974 to 1994. Capaul et al. (1993) find 0.11% of monthly value premium from 1981 to 1992 and Ali, Hwang and Trombley (2003) observe 1.68% of yearly value premium from 1976 to 1997. Lakonishok et al. (1994) justify the value effect for the U.S. market. Lo and MacKinley (1990) and Banz and Breen (1986) argue that the value premium may be driven by the dataset problems. While most of the studies on value effect use COMPUSTAT database, Davis (1994) use another dataset[17] and still justify the existence of the value effect from 1940 to 1963.

According to FF (1992), B/M proxies an underlying risk factor that is yet to be observed and which is fundamental to the asset pricing. According to them, β cannot account for the value effect. Chan and Chen (1991) reveal that it is the distress factor, namely the low earnings[18], and low productive ability of value firms which creates the co-movement among their returns. Analogously, FF (1995) show that a portfolio consisting of value stocks have lower average earnings[19] compared to a portfolio consisting of growth stocks. In addition, they argue that "…high B/M is typical of firms that are relatively distressed" (FF, 1995: 132). In explaining value premium, Chan and Chen (1991) follow Ball (1978) and argue that the value stocks perceived riskier by investors and their future cash flow stream discounted with higher discount rate.

Not all the pricing stories are rational, however. Lakonishok et al. (1994) argue that value premium is a result of opportunist "contrarian" investors betting against "naïve" (Lakonishok et al., 1994: 1542)[20]. Ali et al. (2003) show that not only individuals but the institutional investors are also prone to such biases. According to their results, institutional investors avoid value stocks, resulting in a drop in their prices which crates the value premium[21].

Whatever the underlying reason behind the value effect of the U.S. stocks, the B/M variable has a predictive power on the cross-section of stock returns. This effect is pronounced, observed extensively for a long period of time and it is robust against the size and β effects. What we know about the value stocks is clear; (i) investors price value and

[17] Davis (1994) used Moody's industrial manuals to test whether B/M, earnings yield (i.e earnings/price) and cash flow yield (i.e. cash flow/price) effects existent when data source other than COMPUSTAT is used. Author motvated by data snooping bias, suggested by Lo and MacKinley (1990), survivorship bias and lookahead bias, suggested by Banz and Breen (1986), of the COMPUSTAT database.

[18] Lakonishok et al. (1994) also show that value stocks have low earnings.

[19] Chen and Zhang (1998) also show that value stocks are usually distressed with high financial leverage, high historical dividend cuts and uncertain earnings in the U.S., Japan, Malaysia and Hong Kong markets.

[20] See De Bondt and Thaler (1985) for further discussion on this issue.

[21] See La Porta (1996) and Schleifer and Vishny (1997) for other behavioral explanations on the value premium.

growth stocks rationally for at least five years before and four years after the portfolio formation period (FF, 1995: 132), (ii) value stocks have lower earnings (FF, 1992: 452), (iii) CAPM fail against the value effect in empirical tests (Chan and Chen, 1991; FF, 1992, 1995 and 1998) and a factor that mimic the value investment effect can explain the co-variation between the returns of value stocks (FF, 1993).

Hypothesis 3a: *Value stocks tend to be riskier with low earnings and high D/E ratio.*

Hypothesis 3b: *The CAPM is miss-specified since B/M ratio is positively related with stock returns.*

2.3.1. Value Effect in Non-U.S. Developed Markets

FF (1998) justify the value effect in eleven out of twelve developed international markets[22]. According to their results, constructing zero-investment portfolios of value stocks provides average annual premiums as large as 12.32% in Australia, 9.85% in Japan and 9.67% in Singapore[23] from 1974 to 1994. However, like the size effect, value effect is not observed in Italy. Results from Chen and Zhang (1998) on the value effect of Hong Kong and Japanese markets is analogous. They show that, taking short and long positions in the extreme decile portfolios, based on five deciles strategy, provides monthly premiums of 0.71% and 0.89%, for Hong Kong and Japan, respectively[24]. Additionally, Capaul et al. (1993) justify the profitability of value investing in France, Germany, Switzerland, Japan, the U.K. and the U.S. markets from 1981 to 1992. Their results are robust against market β, and the value spreads for all those five markets are larger than that of the U.S. market. Results from Anderson and Brooks (2006) for the U.K. market is almost similar from 1975 to 2003, concluding that the annual value premium is about 6 percent. Haugen and Baker (1996) reveal similar patterns in France, Japan, Germany and

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[22] Australia, Belgium, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Singapore, Sweden, Switzerland, and the UK.
[23] Their value premium represents annual differences between returns on highest 30% and lowest 30% portfolios sorted by B/M. For details survey page 1980, Table 3 in FF (1998).
[24] For details please see Chan and Zhang (1998), page 506, Table 2 and page 508 Table 3.

the U.K. markets. Similarly, Chan, Hamao and Lakonishok (1991) justify the value effect for the Japanese market from 1971 to 1988. The results of FF (2012) on the value effect in the Japanese market is supportive. In addition, they show that a value portfolio consisting stocks of the developed markets from four regions, namely, North America, EU, Japan, and Asia Pacific, is profitable from 1990 to 2011[25].

2.3.2. Value Effect in Developing Markets

Rouwenhorst (1999) examine the profitability of value investment strategy in twenty developing markets[26] from 1987 to 1995 and observe value premium in sixteen out of twenty. According to his results, financing an E-W portfolio consisting of high B/M stocks (top 30% in sorts) with a portfolio consisting of low B/M stocks (bottom 30% in sorts), provides monthly premiums of 1.68% in Argentina, 3.94% in Brazil, 2.86% in Turkey and 2.31% in Zimbabwe[27]. However, these premiums are barely two standard errors away from zero[28]. In addition, FF (1998) show that constructing a zero-investment value portfolio consisting of stocks from sixteen developing markets provide a V-W average annual premium of 16.91% and an E-W average annual premium of 14.13 percent[29]. Their results related with the developing markets supports those of Rowenhorst (1999). Chen and Zhang (1998) reveal consistent results in Malaysia and Taiwan based on a five deciles E-W extreme portfolio investment strategy.

More recently, Çakici et al. (2013) find value effect in eighteen developing markets from three regions, namely, Asia, Latin America and Eastern Europe, from 1991 to 2011. Finally, Hasan et al. (2015) and Lischewski and Voronkova (2012) provide

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[25] For details see FF (2012), page 461, Table 1.

[26] Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, and Zimbabwe.

[27] For details see Rouwenhorst (1999), page 1450, Table 3.

[28] The reason may be attributable to the high SD of constructed portfolios, as FF (1993) described in their seminal paper. This finding is a common problem for developing markets.

[29] Premiums represents average differences between the returns on highest 30% of portfolio sorted by B/M minus returns on lowest 30% portfolio sorted by B/M. For details, see, FF (1998), page 1994, Table 7.

evidence on value effect from Bangladesh (from 2004 to 2013) and Poland (from 1996 to 2009), respectively.

2.4. MOMENTUM AND EXPECTED-RETURNS

Jegadeesh and Titman (1993) reveal that the short to medium term past stock performances tend to continue in AMEX and NYSE from 1965 to 1989. For example, a portfolio constructed from the stocks which perform good in the past six-month period provide annual abnormal return of 9.5% for a year of holding period, and this momentum effect is robust against β. In a follow-up study, Jegadessh and Titman (2001) show that the momentum effect exists from 1965 to 1998. Conrad and Kaul (1998) and Chan et al. (1996) justify the momentum effect from 1926 to 1989 and from 1977 to 1993, respectively. According to Chan et al. (1996) buying winners and selling losers of the prior six-month period provide 15.4% of average return for a year of holding period. Additionally, FF (2008) justify the robustness of the momentum effect against different size groups.

Several explanations emerge to explain the momentum effect. For example, Jegadeesh and Titman (1993), Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) and Hong and Stain (1999) argue that the momentum effect is a product of investor underreaction, that is the slow incorporation of fundamentals to common stock prices. As a result, over a medium to short time period stock prices tend to persist and they exhibit a positive autocorrelation. According to Jegadeesh and Titman (2001: 719), behavioral models are promising, whereas their ability critically depends on the sampling period and the sample[30]. In contrast, according Conrad and Kaul (1998), there is an underlying risk factor which is responsible from the co-variation between momentum stocks. According to Johnson (2002), this risk might be the volatility in the recent historical prices.

[30] Survey Cooper, Gutierrez Jr. and Hameed (2004), Hong and Stain (1999), and Jegadeesh and Titman (2001) for richer explanations on the behavioral issues underlying the momentum patterns.

Nevertheless, consistent with the findings of FF (1996), Jegadeesh and Titman (2001) find that the traditional risk factors of the U.S. market, i.e. size and value, cannot explain the momentum effect. Chan et al. (1996) fail to associate momentum returns with size, value and past earnings, they find supportive patterns for the underreaction hypothesis. Results from Chan, Jegadeesh and Lakonishok (1999) also support the underreaction hypothesis. In addition, results from Hon and Tonks (2003), Griffin, Ji and Martin (2003) and Rouwenhort (1998) related with the international momentum effect have similar findings.

According to the empirical evidence, the underreaction hypothesis is promising. The traditional pricing models cannot account for the momentum effect. In contrast, behavioral models have prospect, whereas their success depends on the period and sample (Jegadeesh and Titman, 2001). However, the momentum anomaly is persistent, it is observed for a long period. In addition, FF (2008) justify the momentum anomaly among most liquid and mostly analyzed stocks (stocks that are larger than the median NYSE market capitalization); hence, underreaction to the fundamentals of these highly liquid stocks is unlikely. Moreover, Conrad and Kaul (1998) emphasize the co-movements among momentum stocks. This co-movement is due to the recent price growth (Johnson, 2002), not with past earnings (Chan et al., 1999). Motivated from the rational pricing equation of FF (2006), the CBOP factor may have the potential to explain the momentum anomaly.

Hypothesis 4a: *Trading on historical return data is profitable.*

Hypothesis 4b: *The CAPM is miss-specified since momentum is positively related with stock returns.*

2.4.1. Momentum Effect in Non-U.S. Developed Markets

Profitability of the momentum trading is also observed in international developed markets other than the U.S. market. Rouwenhorst (1998) investigate the momentum effect for twelve European markets[31] from 1980 to 1995 and show that holding a diversified portfolio including winner stocks provide a significant average monthly premium of 1.16 percent. This momentum effect is also observed when these markets examined individually. For example, financing a portfolio consisting of the winner stocks with a portfolio consisting of the loser stocks in Belgium, Denmark, France, the Netherlands and Spain provides average monthly premiums of 1.10%, 1.09%, 0.97%, 1.26%, and 1.32%, respectively[32]. Novak and Petr (2010) document the profitability of the momentum investing in Sweden from 1979 to 2005. Results from Griffin et al. (2003) is consistent for the other developed markets[33]. In contrast, their results indicate a weak momentum effect for Japan. In addition, FF (2012) document momentum premium in North America, Europe, Asia Pacific, and Japan. However, consistently, their momentum premium in Japan is too small, such as 0.08%, and observed only among big stocks[34]. Çakici et al. (2013) justify the profitability of momentum investing using a global portfolio composed of stocks from several developed markets. According to their results, the monthly momentum premium of their diversified portfolio from 1991 to 2011 is 0.63%. In contrast, Hon and Tonks (2003) show that the momentum effect is relatively new for the U.K. market common stocks. In addition, they also fail to associate momentum premium with other risk factors such as size and β.

2.4.2. Momentum Effect in Developing Markets

In his study, Rouwenhorst (1999) observe the momentum effect for the seventeen of the twenty emerging markets[35] from 1987 to 1995. He documents average

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[31] Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK.

[32] Rouwenhorst (1998) construct E-W portfolios based on ten quintiles and prior six-month performances. Momentum premium represents difference between average monthly returns on a portfolio composed of winner stocks (top 10%) minus average monthly returns on a portfolio composed of loser stocks (bottom 10%). For details survey Rouwenhorst (1998), page 274, Table 3.

[33] Canada, Finland, Ireland, Japan, New Zealand and Singapore. For details survey in Griffin et al. (2003), pages 2519-2521, Table 1.

[34] For details survey FF (2012), page 461, Table 1.

[35] Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe.

monthly premiums on momentum investing as 1.37%, 2.09% and 1.43% for Chile, Colombia and Nigeria, respectively. These premiums are larger than the premiums observed for the developed markets. However, he argues that the momentum strategy cannot be used for the markets such as Argentina, Indonesia and Taiwan[36]. Additionally, he emphasizes on the similarity of momentum patterns between developed and developing economies. Griffin et al. (2003) obtain consistent patterns from several other developing markets, excluding China[37]. Muga and Santamaria (2007) find that momentum investing is also profitable for some markets such as Brazil, Argentina, Chile and Mexico from 1994 to 2005.

Recently, Çakici et al. (2013) document the effect of investing in a global momentum portfolio composed of stocks from eighteen developing markets from regions such Asia, Latin America and Eastern Europe. They determine an investing strategy depending on the prior twelve-month and three quintiles. Their global portfolio provides average monthly premium of 0.86% from 1991 to 2011. When they try to investigate the momentum premiums for the portfolios consisting these regions separately, they observe that the portfolios consisting stocks from Asia and Latin America provide higher premiums which are statistically significant. However, they do not observe the momentum effect for the Eastern Europe[38].

2.5. PROFITABILITY AND EXPECTED-RETURNS

As an early study, Ball and Brown (1968) reveal a positive relationship between net income and E-Rs for the U.S. securities from 1946 to 1966. According to them the content carried by net income is fundamental to common stock pricing. Haugen and Baker

[36] Rouwenhorst (1999) construct E-W portfolios based on prior six-month performances, removes top and bottom 5% and identify three quintiles as winners (top 30%), average (middle 30%) and losers (bottom 30%). Momentum premium represents monthly average return on a portfolio of winner stocks minus monthly average return on a portfolio of looser stocks. For details survey Rouwenhorts (1999), page 1450, Table 3.

[37] Different than Rouwenhorts (1999), Griffin et al. (2003) examined China, Egypt, Peru, and South Africa. For details survey pages 2519-2521, Table 1.

[38] For details survey Çakici et al. (2013), page 53, Table 2.

(1996) find similar results from 1979 to 1993. In addition, Chan et al. (1996) show that earnings surprises can predict E-Rs. Ball (1992) document the profitability of treading on historical earnings information in the U.S. market. Analogously, FF (2006) find a positive relationship between earnings before extraordinary items and E-Rs by employing a cross-sectional regression analysis. However, FF (2008) fail to attain the same strong relationship in the portfolio sorts. According to their results, the relationship between profitability and E-R is not linear and provides only 1 percent of premium annually.

The relationship between net income and E-Rs and earnings before extraordinary items and E-Rs is not that pronounced. According to Ball and Brown (1968: 160), net income is a collection of heterogeneous items which is resulted from the dissimilarities in the accounting practices. Therefore, its ability to predict future returns is restricted. In contrast, Novy-Marx (2013: 2) argue that the gross profits (revenues reduced by cost of goods sold, hereafter GP)[39] is a cleaner measure of the economic profitability. He shows that the GP has a strong linear relationship with E-Rs compared to those of net income and earnings from 1963 to 2010. He compares free cash flows and earnings before extraordinary items those are scaled by book equity and GP which is scaled by book assets and argue that the GP is superior in predicting E-Rs. However, according to Ball et al. (2015: 226), when consistent deflators are used, GP lost its superiority. They offer another profitability measure, namely the operating profitability (GP reduced by selling and administrative expenses net of research and development expenditures, hereafter OP)[40], which predicts E-Rs better than the GP. According to Ball et al. (2015), OP is more informative since selling, general and administrative expenses represents important portion of operating costs. Recently, Ball et al. (2016) show that a CBOP, OP with reduced

[39] Novy Marx (2013) argue that the GP is a cleaner measure of true economic profitability since it does not include cost items like advertising, sales force commission, and research and development that lead to higher current and future revenues, but lower current bottom line. Earnings may lead low revenue firms to apperar more prfitable than firms investing for the future.

[40] Ball et al. (2015) reduced GP by selling, general and administrative expenses net of research and development expenditures (R&D) to arrive the OP. Selling general and administrative expenses are actual reporting numbers. However, although research and development expenditures are reported as they are incurred they are expenditures to generate future revenues. Therefore, OP incorporating R&D expenses is more informative.

ARs, has a stronger relationship with E-Rs. It is important to add that the CAPM and FF3M cannot explain the GP, OP and CBOP premiums.

Analogous to Ball et al. (2016), Fairfield, Whisenant and Yuhn (2003) show that earnings have two components, ARs (i.e. adjustments made by accountants to transform operating cash flows into earnings) and cash flows (i.e. earnings net of ARs). These components are oppositely related with E-Rs, ARs are negatively related, while cash flows are positively related[41].

The results of the studies examining the predictive ability of cash-based and ARs-based earnings measures are conflict. Dechow (1994) examine earnings and net cash flows and show that under some instances, where; the performance measurement interval is short, firms' investment and financing activities are volatile, and their operating cycle is longer, ARs-based profitability measure performs better. However, the results of Ball et al. (2016) suggest that the profitability measure net of ARs, the CBOP, is more informative about E-Rs in usual circumstances. The relationship between profitability measures and E-Rs is still puzzling for the BIST, however.

According to FF (2006) the positive relationship between profitability and E-Rs can be explained by reorganizing the *DDM* (see Equation 1). Under the clean surplus accounting assumption, dividends can be represented by the expected future earnings minus expected yearly change in the book value of equity (see Equation 2). Deflating both sides of the equation 2 by time t book value of equity gives equation 3. Equation 3 speculates a positive relationship between expected profitability and E-Rs since there will be more cash dividends expected by shareholders in the case of higher expected profits. In this theoretical framework, we argue that the CBOP has more potential in predicting future returns than the earning-based profitability variables since it is completely free from ARs which are not relevant to the dividends[42].

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41 For ARs see Ball et al. (2016), Fairfield et al. (2003), Özkan and Kayali (2015), and Sloan (1996). For earnings see Ball et al. (2016), Cohen, Gompers and Vuolteenaho (2002) and Novy-Marx (2013).

42 There are behavioral explanations related with the association between earnings measures and E-Rs. According to Cohen et al. (2002) the relationship between E-Rs and earnings is the result of underreaction of irrationals to the fundamental cash flow announcements. While according to Sloan (1996) it is the overvaluation of ARs components of earnings.

Consequently, empirical findings of Ball et al. (2015), FF (2008) and Lakonishok et al. (1994) suggest that the earnings before extraordinary items is insufficient in predicting E-Rs, they perform poor in the sorts and add relatively little over the size and value premiums). Additionally, spread for the earnings is mostly concentrate on small stocks (Lakonishok et al., 1994). According to Ball and Brown (1968) the reason is the heterogenous identity of net income. In contrast, Novy-Marx (2013) show that the *GP* predicts E-Rs properly, since it is *cleaner* in the sense that it adjusted for only cost of goods sold. However, according to him, the rational pricing kernel cannot explain patterns in the *GP*. Whereas, Ball et al. (2016) show that CBOP predicts E-Rs at least ten years ahead [43] and the CBOP produce larger premiums on extreme decile profitability investment strategy compared with the earnings based investment strategies. Therefore, we argue that the CBOP has the potential to proxy the numerator of equation 3 since it is completely free form ARs.

Hypothesis 5a: *Profitability has a positive linear relationship with E-Rs as equation 3 speculates.*

Hypothesis 5b: *Profitable firms have lower average B/M ratio as equation 3 speculates.*

Hypothesis 5c: *CAPM cannot explain the relationship between profitability and E-Rs; hence, the CAPM is miss specified.*

Hypothesis 5d: *The CBOP is better in predicting E-Rs compared to earnings based profitability variables.*

Hypothesis 5e: *There is a negative relationship between ARs and E-Rs.*

2.5.1. Profitability Effect in Non-U.S. Developed Markets

Haugen and Baker (1996) observe the profitability effect in France, Germany, Japan and the U.K. markets. Ammann et al. (2012) provide similar results for a portfolio

[43] Persistency of the profitability anomaly also emphasized by Ball (1992), Ball et al. (2015) and FF (1995 and 2006).

consisting of stocks from ten developed EU markets[44], their annual profitability premium is 4%[45] from 1990 to 2006. Novy-Marx (2013) construct a portfolio sorted by *GP* consisting the stocks from nineteen developed markets[46] and document an average monthly GP premium of 0.79%[47] from 1990 to 2009. More importantly, the traditional FF3M cannot explain this GP premium. In contrast, the model indicates larger monthly GP premium (alpha, $\alpha = 0.99$).

Nichol and Dowling (2014) show that the profitability factor, constructed following FF (2015), provides an average monthly premium of 0.41% from 2002 and 2003 in the U.K. market. FF (2017) investigate twenty-three developed markets from four regions[48] and document positive premiums on profitability mimicking factors constructed consisting the stocks from Asia Pacific, EU and North America from 1990 to 2015. However, the premium on a profitability mimicking factor in Japan is only 0.13% per month.

On the other hand, Papanastasopoulos (2014) investigate sixteen EU markets on the ARs anomaly[49] and justify it in fifteen of them. He shows that the annual AR premium on the global portfolio including stocks from these markets is 6.2 percent[50].

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[44] Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain.

[45] Authors use ROA (net income deflated by total assets) to rank stocks and allocate them into ten deciles. Profitability premium represents monthly return on a portfolio of high ROA stocks minus monthly return on a portfolio of low ROA stocks. For details see Ammann et al. (2012), page 1859, Table 3.

[46] Australia, Austria, Belgium, Denmark, Finland, France, Germany, the UK, Hong Kong, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden and Switzerland.

[47] Novy-Marx (2013) construct V-W portfolio based on GP and identify five quintiles using the breakpoints of NYSE. His GP premium represents monthly average returns on a portfolio of profitable stocks minus monthly average returns on a portfolio of unprofitable stocks. For details survey Novy-Marx (2013), page 9, Table 5.

[48] Regions includes North America, Japan, Asia Pacific and EU. They examined same markets with FF (2012).

[49] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK.

[50] Papanastasopoulos (2014) use five deciles from 1988 to 2009. Premium on the hedge portfolio represents E-W monthly average returns on low ARs portfolio minus high ARs portfolio. For details survey Papanastasopoulos (2014), page 747, Table 3.

2.5.2. Profitability Effect in Developing Markets

Zaremba and Czapkiewicz (2017) examine a wide variety of market anomalies for markets such as Czech Republic, Hungary, Poland, Russia, and Turkey. They find that taking a long and a short position in extreme decile portfolios sorted by profitability[51] provide positive premium from 1997 to 2015. Chiah et al. (2016) obtain similar results for the Australian market from 1982 to 2013. They show that a profitability mimicking factor has an average monthly premium of 0.59 percent[52]. In addition, Guo et al. (2017) investigate Chinese market and reveal that a profitability factor constructed based on the ROE has a monthly premium of 0.55% from 1995 to 2015[53].

2.6. CORPORATE INVESTMENT AND EXPECTED-RETURNS

Consistent with the speculations of the valuation equation of FF (2006), empirical evidence suggests a negative relationship between the average returns and corporate investment. According to the findings of Lakonishok et al. (1994), E-Rs on the U.S. common stocks decrease with sales growth from 1971 to 1988. In addition, Titman et al. (2004) document a negative relationship between capital investment and E-Rs. According to their results, capital investment growth (hereafter IG) anomaly is robust against size, value and momentum variables from 1973 to 1996. Fairfield et al. (2003) observe that the growth in long-term net operating assets is negatively related with E-Rs. FF (2006 and 2015) reveal a negative relationship between the total assets growth and E-Rs. According to Cooper, Gülen and Schill (2008), total book assets is the most informative growth measure since it is complete, in the sense that it reflects the entire changes in both investing and financing activities.

Xing (2008) show that a zero-investment low capital expenditure portfolio has an average monthly premium of 0.58% from 1964 to 2003. The results of FF (2015 and

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[51] See Zaremba and Czapkiewicz (2017), page 8, Table 3 for details on the profitability strategies and premiums.

[52] See Chiah et al. (2016), page 604, Table 2 for details.

[53] See Guo et al. (2017), page 91, Table 4.

2016) on the profitability of asset growth (hereafter AG) investment strategy is almost similar, their investment factor provides an average monthly premium of about 0.32% from 1963 to 2014 in the U.S. market. In addition, according to Cooper et al. (2008) a zero-investment low AG portfolio has an annual premium of about 10% from 1963 to 2003.

The reason underlying the investment anomaly is challenging. Consistent with their valuation equation (Equations 2 and 3), FF (2006) show that the growth rate in the total assets can predict E-Rs in a cross-sectional regression analysis. In contrast, Liu, Whited and Zhang (2009) explain the corporate investment effect under the *q*-theory of investment, in which managers tend to invest more when the required rate of return on the common stocks of a firm, or alternatively its cost of capital, is low. Therefore, the AG rate contains information related with the discount rate. Titman, Wei and Xie (2013) provide support for the q-theory. Whereas, according to Cooper et al. (2008), their findings cannot be explained by the risk-based models and robust against well known risk proxies[54]. Whereas, to the best of our knowledge the corporate investment effect has never been examined for the BIST.

Hypothesis 6a: *Corporate investment has a negative linear relationship with E-Rs as equation 3 speculates.*

Hypothesis 6b: *CAPM cannot explain the relationship between corporate investment and E-Rs; hence, the CAPM is miss specified.*

2.6.1. Investment Effect in Non-U.S. Developed Markets

Chiah et al. (2016) investigate Australian market and show that a local investment factor has an average monthly premium of 0.42% from 1982 to 2013. FF (2017) observe the AG in twenty-two stock markets located in Asia Pacific, EU and North America from 1990 to 2015. However, according to them the premium on the investment factor in Japan is only 0.08% per month. In contrast, Nicol and Dowling (2014) fail to

[54] See Lakonishok et al. (1994) and Titman et al. (2004) for alternative explanations, particularly behavioral, on the relationship between investment and average stock returns.

reveal any significant premium on total AG and fixed AG investment strategies in the U.K. during 2002 to 2013. Whereas, Gray and Johnson (2011) reveal a strong AG effect in the Australian market from 1983 to 2007. Yao et al. (2011) justify the AG effect in Asian markets including the Japan. According to their results, AG premium in Japan is 0.74% and it is significant. In addition, Panastasopoulos (2017) reveal statistically significant AG effect for developed EU markets. Finally, Titman et al. (2013) observe the AG effect for twenty-six developed markets[55].

2.6.2. Investment Effect in Developing Markets

Results from the developing markets related with the corporate investment effect is mixed. For instance, Zaremba and Czapkiewicz (2017) examine the investment effect in five developing markets. According to their results, the investment premiums is weak in these developing markets from 1997 to 2015[56]. Analogously, Guo et al. (2017) fail to observe any investment effect[57] in the Chinese market from 1995 to 2015. In contrast, results from Wang et al. (2015) indicate that the AG premium, the monthly spread on the returns between a portfolio consisting of low AG stocks and a portfolio consisting of high AG stocks, is 0.8% from 1996 to 2010. Finally, Titman et al. (2013) show that the AG effect is statistically weaker, yet it is economically present in fourteen developing markets[58].

2.7. FACTOR MODELS OF ASSET PRICING

Empirical evidence from Ball et al. (2015 and 2016), Banz (1981), Basu (1983), Bhandri (1988), Chan et al. (1985), Cooper et al. (2008), Reinganum (1981b) and Novy-

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[55] For details see Titman et al. (2013) Table 3, page 1415.
[56] They investigate Czech Republic, Hungary, Poland, Russia, and Turkey. Survey Zaremba and Czapkiewicz (2017), page 8, Table 3 for details on the investment strategies and premiums.
[57] Authors investigate the relationship between the growth rate in total book assets and E-Rs and the growth rate between total book equity and E-Rs.
[58] See Watanabe et al. (2013) and Yao et al. (2011) for further evidence on the AG effect from wide range of developed and developing markets.

Marx (2013) suggests that the traditional CAPM (Equation 8) fail to explain average returns on portfolios sorted by considering the firm specific characteristics. The findings of these studies reject the perfect world of CAPM where there is only one source of systematic risk factor and which suffices to explain the movements in the asset prices. Therefore, we refer such pricing irregularities as market *anomalies*. Their nature is anomalous for the CAPM.

Ball (1978), Fama (1991) and FF (1988 and 1993) are supporters that the anomalies, in fact, proxy the effects of unpredictable changes in the underlying fundamental factors, the different sources of *risk*, that is not observed yet. While, according to Banz and Breen (1986), Black (1993) and Lo and MacKinlay (1990) market anomalies are results of data mining and other data related biases. General tendency aimed to resolve and explain these market pricing inefficiencies manifest itself as the incorporation of additional factors to the traditional CAPM equation. Jagannathan (2007: 1627) call such models as "…portfolio return-based models". This section is devoted to these models.

2.7.1. How to Pick-Out and Test Factors?

Financial economics literature suggests dozens of anomalies and plenty of factors. However, it is important to identify the minimum number of factors, for the sake of simplicity and practical issues, that can better explain the movements in the asset prices.

Need for additional factors can be explained by the theories of Merton (1973) and/or Ross (1976) or Huberman and Kandel (1987). According to Merton (1973), whenever holding a well-diversified market portfolio is not enough to embody all the risks, mean-variance optimizers tilt towards additional hedge positions. The sources of these risks are not known yet, but they influence the investment and consumption patterns of investors (also see Ross, 1976). Therefore, pricing factors which can reflect their effect can explain the movements in the common stocks prices as well as the risk variable itself. In this case, additional factor is needed. In this framework, factor models are either consistent with the Intertemporal CAPM (hereafter I-CAPM) of Merton (1973) or the

Arbitrage Pricing Theory of Ross (1976). In contrast, leaning towards Huberman and Kandel (1987), the mean-variance efficient portfolio may be spanning from different combination of the riskless asset, market portfolio, and empirically motivated factors.

In both cases, according to FF (2015: 3), the role of the valuation equation (equation 3) "…is to suggest factors that allow us to capture the expected return effect of state variables without identifying them". According to them, their valuation equation provides guidance in choosing these factors regardless the theory underlying them.

On the other hand, to test the pricing ability of factors, FF (1993) suggests the time series approach for at least two reasons; (i) factor loadings and R^2 of models provide direct evidence related with the ability of factors in capturing the co-variation among securities. This variation resulted from the exposure to an underlying state variable that is not observed yet, and not needed though, whenever the factors are able to reflect their impact. (ii) intercept from the models provide metrics related with the multivariate ability of "…how well different combinations of common factors capture the cross-section of E-Rs" (FF, 1993: 5).

An intercept estimate from a time series model which can capture the variations in the dependent variable should be, statistically speaking, equal to zero (Merton, 1973). Gibbons et al. (1989) has a solution to test this statistical prediction. Their test examines the hypotheses whether implied α values are all statistically indistinguishable from zero (formally $H_0 = \alpha_1 = \alpha_2 = \ldots = \alpha_i = 0$). In other words, the GRS test provide evidence related with the mean-variance efficiency of factors. Therefore, we benefit from GRS test and several other statistics in assessing the pricing ability of models. The details related with the model test statistics are in *Section 3.6*.

2.7.2. The Three-Factor Model of FF

According to the findings from FF (1992) and Renganum (1981b), the ME and B/M performs better than the price to earnings ratio, D/E and earnings yield (i.e. earnings-to-price ratio) in the cross-sectional regressions. Motivated from the success of the ME and B/M and the failure of CAPM in capturing these effects, FF (1993) offer a new model that augments CAPM with two additional factors. They argue that their model is a version of either the I-CAPM or APT. In either case, investors are concerned with hedging against additional systematic risk factors, and their new factors can reflect these effects.

Accordingly, FF3M speculates that the excess E-R on a portfolio or stock, i, can be explained by its exposure to three factors; namely, the market excess return, average returns on a portfolio consisting of small stocks minus average returns on a portfolio consisting of big stocks (SMB, small minus big)[59], and average returns on a portfolio consisting of stocks with a high B/M ratio minus average returns on a portfolio consisting of stocks with a low B/M ratio (HML, high minus low). Formally, expected excess return on i is,

$$E(r_i) - r_f = b_i\left[E(r_m) - r_f\right] + s_i E(SMB) + h_i E(HML) \quad \text{(eq.10)}$$

where, $r_m - r_f$, SMB and HML are expected premiums, b_i, s_i, and h_i are factor loadings (i.e. slopes). In the time series regression,

$$r_i - r_f = \alpha_i + b_i\left(r_m - r_f\right) + s_i SMB + h_i HML + e_{i,t} \quad \text{(eq.11)}$$

where, α_i is the intercept and the final term is residuals with an expected mean of zero. Leaning towards Huberman and Kandel (1987), if these factors can fully describe the average returns, then α_i should be zero in the time series regressions for any set of combination of LHS assets.

The size investment mimicking factor is motivated by the empirical findings of Chan et al. (1985) and Chan and Chen (1991) that the small firms are usually prone to default risk, has higher financial leverage and lower productive ability[60]. Using the SMB in the asset pricing is appropriate since results from Jegadeesh (1992) and FF (1992) indicate that the CAPM cannot account for the co-variation among small stocks.

In a similar manner, high B/M firms are value firms with depressed (Chan and Chen, 1991) and persistently low earnings (FF, 1992: 452). In addition, CAPM fail to reflect the co-variation among the value stocks (FF, 1992, 1995 and 1998). Therefore, usage of factor HML in the pricing equation will be appropriate.

[59] The SMB factor can also be described as zero-cost investment portfolio strategy based on market capitalization. Similar explanation also applies for other factors that will be discussed.
[60] FF (1993) argues that the small capitalization firms can suffer a long term earning depression.

2.7.2.1. Performance of the Three-Factor Model

Short after its establishment, the FF3M has become a norm of asset pricing, both for academics and practitioners. FF (1993) introduce and test the pricing ability of their model against portfolios sorted by size and B/M from 1963 to 1991. They show that their new model performs better than CAPM against the returns of these portfolios. This finding is not surprising since these factors are empirically motivated. However, the model produces conflicting results in out-of-sample tests and mainly fail to explain returns on portfolios sorted by different variables; such as, profitability, ARs, momentum and corporate investment.

For example, results from FF (1996) indicate that the FF3M performs well in explaining returns on portfolios sorted by size, B/M, earnings yield, cash flow yield and sales growth, however, it fails against the momentum effect. This finding is the first, yet not least, evidence that the FF3M is not a complete description of the average returns. More recently, the model is found deficient by Ball et al. (2015 and 2016), Cooper et al. (2008), Novy-Marx (2013) and Xing (2008) in explaining ARs, profitability and AG effects on the common stock returns of the U.S. market. Results from Ball et al. (2015 and 2016) indicate that the model cannot explain OP, CBOP and ARs effects in the U.S. stock returns. Novy-Marx (2013) show that the model fails to account for the returns on portfolios sorted by GP from 1973 to 2010. In addition, Cooper et al. (2008) show that the FF3M produces significant intercepts against the returns on a portfolio consisting of the low AG stocks. Results from Xing (2008) related with the IG effect (i.e. growth rate in the capital expenditure) is analogous. Finally, according to the results from Hou et al. (2016), the FF3M fail to explain returns on zero-investment portfolios which are constructed according to different profitability and AG variables and different momentum strategies in the U.S. market[61].

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[61] For details see Hou et al. (2016), Table 4, page 668-669.

2.7.2.2. International Performance of the Three-Factor Model

The empirical performance of the model in the international markets is more problematic.

Drew and Veeraraghavan (2002) investigate Malaysian stock market and argue that the FF3M is effective in explaining returns on spanning portfolios used to construct factors of the model from 1992 to 1999. However, model extract significant α values in two out of six cases. Moreover, they did not compare the performance of the FF3M with alternative models of asset pricing. Vo (2015) examine the ability of FF3M for the Australian market during the period 2009 to 2014 and reveal that the model produces mixed results depending on the portfolio formation methodology. Additionally, according to him, the SMB factor cannot be considered in the security pricing in Australia. Novy-Marx (2013) examine a wide range international developed markets[62] and show that the FF3M does not explain the returns on portfolios sorted according to GP. Finally, results from Yao et al. (2011) indicate that the FF3M cannot explain the AG anomaly in the nine Asian markets[63]. In contrast, Gaunt (2004) show that the FF3M performs better than the CAPM in explaining returns on the portfolios sorted by B/M and size from 1991 to 2000.

2.7.3. The Five-Factor Model of FF

Throughout time, as additional market anomalies have been discovered, it has been understood that the FF3M is not a complete description of average returns. In this manner, FF (2015) augment two additional factors, profitability and investment, to the FF3M equation. According to them, rather than being arbitrary, the two additional factors are natural choices which are suggested by the pricing equation (for details see Equations 2 and 3).

[62] Australia, Austria, Belgium, Denmark, Finland, France, Germany, the UK, Hong Kong, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden and Switzerland.
[63] China, Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand

Accordingly, they offer the FF5M which speculates that a complete description for E-Rs in excess of riskless rate on asset i can be provided by its exposure to the five factors; namely, the market excess return, SMB, HML, average returns on a portfolio consisting of profitable stocks minus average returns on a portfolio consisting of unprofitable stocks (robust minus weak, hereafter RMW), and average returns on a portfolio consisting of low investment stocks minus average returns on a portfolio consisting of high investment stocks (conservative minus aggressive, hereafter CMA). Formally, expected return on i is,

$$E(r_i) - r_f = b_i\left[E(r_m) - r_f\right] + s_i E(SMB) + h_i E(HML) + r_i E(RMW) + c_i E(CMA) \quad \text{(eq.12)}$$

where, $r_m - r_f$, SMB and HML, RMW and CMA are expected premiums and b_i, s_i, h_i, r_i, and c_i, are factor loadings (i.e. slopes). For the time series version see Equation 4.

Leaning towards Huberman and Kandel (1987), if these factors can fully describe the average returns, then α_i should be zero in the time series regressions for any set of combination of LHS assets.

The use of additional two factors, namely, the RMW and CMA, is motivated by the pricing equations 2 and 3. In addition, according to the findings of Ball et al. (2015 and 2016), Novy-Marx (2013) and Titman et al. (2004), CAPM, and FF3M fail to reflect profitable and low AG firm effects. Therefore, considering RMW and CMA in the pricing equation will be appropriate.

2.7.3.1. Performance of the Five-Factor Model

FF (2015) assess their new model against the returns on the portfolios sorted by size-profitability, size-investment and size-B/M variables. Based on several model performance statistics, FF5M produces lower alpha dispersions and lower GRS statistics; hence, it performs better than the FF3M in capturing average returns on size and B/M, size and profitability and size and investment portfolios. However, according to their findings, the inclusion of the factors RMW and CMA displaces the famous factor HML since they observe a strong positive correlation coefficient between the returns of factors CMA and

HML. Additionally, according to them, FF5M cannot explain the returns of small stocks with low profits and high corporate investment level. More recently, FF (2016) test their new model against several unrelated market anomalies. In their recent paper, they test the performance of the FF5M against the returns of portfolios sorted by size and beta, size and net share issues, size and residual variance, size and ARs and size and momentum. Their results indicate that the FF5M performs better than FF3M in describing average returns for most of these portfolios. But, like the FF3M, FF5M cannot describe the returns of the portfolios sorted by size-ARs and size-momentum; hence, it cannot be regarded as a complete description for average returns on the U.S. market common stocks.

2.7.3.2. International Performance of the Five-Factor Model

FF (2017) test their new model in markets from Asia Pacific, Europe, Japan and North American. Their results imply that their new model performs better than the FF3M from 1990 to 2015. However, analogously, the FF5M cannot explain the returns of small stocks with low profits and high level of corporate investment. They test their model against the returns on portfolios representing raw versions of its factors. Guo et al. (2017) assess the FF5M in the Chinese market from 1995 to 2015. They find that the market does not exhibit the investment effect. Accordingly, model including traditional three factors and the profitability factor performs better than the FF5M and FF3M. Their test portfolios also represent the raw versions of the model's factors. Zaremba and Czapkiewicz (2017) compare the performances of CAPM, FF3M, and FF5M on a wide range of market anomalies[64] by using stocks from Czech Republic, Hungary, Poland, Russia, and Turkey from 1997 to 2015. According to their results, the FF5M produces the most favorable GRS statistics against the returns on univariate portfolios sorted by related and unrelated anomaly variables. However, their results indicate that the factor loading of the RMW and CMA is insignificant in most of the cases[65]. Nichol and Dowling (2014) provide evidence from the U.K. and reveal that the FF5M performs better than the FF3M from 2002 to 2013.

[64] See Zarembe and Czapkiewicz (2017), Table 3, page 8 for details.
[65] See Zarembe and Czapkiewicz (2017), Table 6, page 13 for details.

Finally, Chiah et al. (2016) assess the FF5M for the Australian market from 1982 to 2013. Their results indicate that the model can explain the returns on portfolios representing raw versions of its factors. In their tests, the HML factor is found as significant.

2.7.4. The Q-Factor Model

Empirical failure of the factor HML motivates Hou et al. (2016), and they suggest a new model, namely, the q-factor model. Theoretical framework underlying their model is the "neoclassical q-theory of the investment" (Hou et al., 2016: 651).

According to the q-theory of investment, the corporate investment and profitability (i.e. ROE) of a firm reveals information about firm's cost of capital. They argue that, whenever a firm's investment level is low given its level of expected profits, the cost of capital is high. In such a case, the value of future benefits from an investment will be low. In addition, when expected profits are high but the corporate investment is low, the cost of capital is high and the future benefits from an investment will be low again. According to their rational pricing equation, there is a negative relationship between E-Rs and corporate investment and there is a positive relationship between E-Rs and profitability[66]. The q-factor model speculates that the excess returns on any asset, *i,* can be explained by its exposure to four factors; the market excess return, SMB, RMW and CMA. Formally, expected return on i is,

$$E(r_i) - r_f = b_i\left[E(r_m) - r_f\right] + s_iE(SMB) + r_iE(RMW) + c_iE(CMA) \qquad \text{(eq.13)}$$

where, $r_m - r_f$, SMB and RMW and CMA are expected premiums and b_i, s_i, r_i, and c_i, are factor loadings (i.e. slopes). In the time series regression,

$$r_i - r_f = \alpha_i + b_i\left(r_m - r_f\right) + s_iSMB + r_iRMW + c_iCMA + e_{i,t} \qquad \text{(eq.14)}$$

where, α_i is the intercept and the final term is residuals with an expected mean of zero. Leaning towards Huberman and Kandel (1987), if these factors can fully describe

66 See, Hou et al. (2016), page 655, equation 4.

the average returns, then α_i should be zero in the time series regressions for any set of combination of LHS assets.

The q-factor model excludes the factor HML since according to their spanning tests and correlations results, the information content of the HML can be subsumed by the q-factors.

2.7.4.1. Performance of the Q-Factor Model

Hou et al. (2016) assess the performance of their model on a wide range of market anomalies in the U.S. from 1972 to 2012. According to their results, the model can explain all the anomalies that FF3M explains. Moreover, q-factor model can also explain market anomalies such as, prior returns, profitability and investment. However, it faces difficulty in explaining returns on portfolios sorted by ARs. In addition, results from FF (2015) indicate that a four-factor model that drops factor HML performs as well as the FF5M. Nonetheless, to the best of our knowledge the Q-Factor model have not been tested for an emerging market.

2.8. MARKET ANOMALIES IN BIST

Empirical studies concerning with the anomalies of BIST common stocks pricing has mixed results. For example, according to Rouwenhorts (1999), from 1989 to 2001, small stocks, value stocks and momentum stocks provide average monthly premiums of 0.72%, 2.86% and 0.48%, respectively. These premiums are economically large, whereas, they all are insignificant due to the high SD of the portfolio returns. Aksu and Önder (2003) observe the size and value effects from 1993 to 1997. By using a panel regression approach, Öztürk and Yilmaz (2015) reveal a positive relationship between B/M and average returns, whereas, a negative relationship between ME and average returns from 2003 to 2013. Bildik and Gülay (2007) document the profitability of small and value investing from 1991 to 2000. In contrast, Atilgan, Demirtaş and Günaydin (2016) examine the cross-sectional relationship between E-Rs and illiquidity. In their study, they use size, value and momentum as control variables from 2002 to 2012. Only the illiquidity measures found statistically significant in the FM (1973) regression[67]. Yüksel (2013) observe that a portfolio consisting of big and growth stocks provide higher returns than a portfolio consisting of small and value stocks from 2001 to 2012. Ersalan (2013) and Gönenç and Karan (2003) find that there exists no size and value effects in the BIST. While, Yildirim (2004) argue that the size and value effects depend on the overall market conditions.

On the other hand, Ersoy and Ünlü (2013) justify the momentum effect for the BIST. According to them, constructing a zero-investment portfolio of winner stocks based on prior six-month performances and holding it for the following six-month provide premiums from 1995 to 2010. They show that this strategy holds for stocks with different size and B/M deciles. In contrast, Bildik and Gülay (2007) fail to observe any momentum effect from 1991 to 2000. They rather document the profitability of contrarian investing strategy.

Finally, Özkan and Kayali (2015) investigate the ARs and cash flows effects and find that the AR anomaly is present for only the profitable firms from 2005 to 2012. While, the profitability anomaly is insignificant.

2.8.1. Applicability of the Factor Models to BIST

The applicability of the factor-based pricing models to an emerging market should be analyzed for their theoretical underpinnings initially since these models are developed for the markets with completely different characteristics. For example, consider the well-known FF3M. Its additional factors, namely the SMB and HML, motivated from the failure of CAPM in explaining the returns on the small and value stocks. In addition, small firms are highly leveraged and value firms are unprofitable in the U.S. market (FF,

[67] According to Rouwenhorts (1999), the use of FM (1973) cross-sectional regression in emerging markets where there are lots of firms with volatile characteristics can provide misleading results. Therefore, portfolio analysis has the potential of reveling more accurate results in emerging markets settings. Although, cross-sectional regression directly provides marginal effect of variables, it is hard to satisfy parametric assumptions of cross-sectional regressions by using firm level data.

1992: 452), and according to the theory this makes them to respond differently to the movements in other unknown systematic risk factors. In contrast, the FF3M used number of times to explain the common stock return in the BIST without any evidence that the small stocks' returns are higher than those of big and value stocks' returns are higher than those of growth and CAPM fail to explain their behavior. In addition, to the best of our knowledge, there exist no study which tests Huberman and Kandel's (1987) hypothesis to examine the combination of the tangency portfolio. In this thesis, we provide evidence related with the motivation of the additional factors as well.

To the best of our knowledge, Aksu and Önder's (2003) work is the only study which investigates the underlying patterns beneath small and value stocks. They show that, small stocks have higher D/E ratio compared to big and value stocks are unprofitable compared to growth. Accordingly, they add local factors of SMB and HML to the traditional CAPM equation and test FF3M in BIST from 1993 to 1997. They examine the model against the portfolios representing raw versions of its factors. However, they did not report extracted intercepts from their model. This shortcoming makes it impossible to make any inference related with their results. On the other hand, according to Yüksel (2013), FF3M cannot predict the average returns, because of low R^2 coefficients and significant α values which has been extracted against the returns on the spanning portfolios of the factors. This is not a surprise since he reports that a spanning portfolio consisting the big and growth stocks provide higher returns than a spanning portfolio consisting the small and value stocks. In contrast, Ünlü (2013) test the applicability of the FF3M in BIST from 1992 to 2011 through applying the spanning portfolio tests on portfolios that are used to construct the factors. They conclude that the model can be used for the BIST.

CHAPTER THREE
METHODOLOGY

This chapter describes our sample, data, portfolio formation procedure and factor calculation.

3.1. SAMPLE

The estimation period of our analysis is from July 2002 to December 2015. We estimate historical βs by using at least eighteen months of excess returns of the four years prior. Accordingly, we form portfolios from July 2006 to December 2015. We start the sample with all the companies traded in BIST during the period from 2005 to 2015. To arrive the ultimate sample, we determine several selection criterions.

We eliminate financial firms following FF (1993 and 2015), and Xing (2008). According to Xing (2008: 1772) it is hard to measure the capital investment performance of the financial firms.

We eliminate firms with negative book value of equity for the portfolio analysis. However, following FF (1993 and 2015), we consider financial firms and firms with negative equity for the market capitalization breakpoint calculations.

To match the sample, we follow Xing (2008) and eliminate firms that are reporting in any month other than December as a fiscal year ending.

We eliminate firms with missing June year t and December year t-1 ME and December year t-1 book value of equity, GP, and book value of total assets following Ball et al. (2015 and 2016).

We eliminate firms without current month's return and those with less than eighteen months prior returns. This criterion can mitigate data related biases suggested by Banz and Breen (1986).

Finally, the Public Disclosure Platform removes the financial reports of failed companies from its datasets; hence, we eliminate firms that have failed[68].

It is important to note that the sampling period is relatively short since listed companies in Turkey start to use consistent reporting standard (i.e. International Financial Reporting Standards - IFRS) following to 2005. Our variables comprise year to year changes in their calculations, therefore, we prefer not to use statements prior to 2005, December[69]. Table 1 provides yearly averages of market value, B/M ratio and β value for the sample firms.

Table 1: Sample Characteristics

Year	*n*	*Market Cap. (TL)*	*USD/TL*	*Market Cap. (USD)*	*Average B/M*	*Average Beta (β)*
2006	133	578,556	1.5797	366,244	0.74	0.95
2007	140	963,296	1.3129	733,716	0.88	0.88
2008	147	730,131	1.2263	595,393	0.77	1.04
2009	147	581,813	1.5344	379,179	1.86	1.10
2010	149	981,817	1.5837	619,952	0.86	1.07
2011	155	1,278,802	1.6259	786,520	0.64	1.10
2012	161	1,256,622	1.8179	691,249	0.85	1.12
2013	175	1,413,032	1.9311	731,724	0.80	0.95
2014	193	1,382,054	2.1296	648,973	1.00	1.00
2015	204	1,466,826	2.6938	544,518	0.78	0.93

Note: We measure the market capitalization (shares outstanding times market price) each year at the end of June and report it in millions. It has been converted into U.S. Dollars using corresponding exchange rate, banknote selling rate, supplied by the Central Bank of Turkey. B/M represents the ratio of December t-1 book value of equity to ME at the last trading day of year t-1. We estimate market beta from at least 18 of the 48 months prior rolling window regression at the end of each June. We use *BIST-100 index* to proxy market portfolio. All the values, except frequencies and exchange rates, represents yearly averages.

Table 1 reports the number of stocks, market capitalization, average B/M ratio and average β values for the sample firms. The average number of sample firms per year is one hundred and sixty. The average B/M ratio and average β reflect the effects of the

[68] We also eliminate Aslan Çimento A.S. (ASLAN) from the sample. Prior to 2012, ASLAN has extremely volatile market characteristics and bouncing monthly returns, and not be able to get listed in the national market for a prolonged period. ASLAN can be characterized as tiny stock with huge market value: hence, eliminated to avoid its inflating and deflating effects on extreme portfolios. The list of sample stocks is available in the Appendix 19.

[69] Year 2004 includes a few earnings items that is not particularly influential in the calculations of CBOP and ARs.

2008 financial crisis. Around 2008, both increased strikingly. The results related with yearly changes in the ME of the sample firms is worrying. Although each year the ME (shares outstanding times market price at the end of each June) of firms traded on BIST increases relative to the Turkish Liras (TL), this is due to both new listings and the appreciation of ME of existing firms. The ME of these firms experiences only marginal changes relative to the U.S. Dollars. Therefore, we adopt U.S. Dollar metrics in the entire analysis to avoid the effect of devaluation of TL against the U.S. Dollars on the results.

3.2. DATA

We obtain monthly stock returns[70], the market equity of June t and December t-1 and the book equity of December t-1[71] from BIST database. We obtain risk-free rate from the Turkish Government Statistical Institute web page which represent the monthly government debt instrument rate. We estimate the market βs at the end of each June. To estimate βs, we use historical monthly excess returns on the *BIST-100* index. For the model estimations, market portfolio represents V-W excess returns on the portfolio of sample stocks that we construct at the end of each June and rebalance annually. Finally, we obtain profitability and investment variables from December t and t-1 financial reports from BIST and Public Disclosure Platform web pages.

3.3. VARIABLES

In this section we describe the variables of the thesis namely profitability, corporate investment, momentum and other variables.

[70] We calculate Monthly stock returns based on U.S. Dollars to purify the effect of devaluation of TL.
[71] In instances where B/E ratio is not available it is calculated following the traditional approach of FF (1993).

3.3.1. Profitability Variables

We employ six different profitability proxies, including both AR based earnings and an operational cash based profits, such as; return on assets (hereafter ROA), return on equity (hereafter ROE), GP, OP, CBOP and ARs. The calculation of the profitability variables are as follows,

ROA; net income of year t deflated by total book assets of year t following Haugen and Baker (1996).

ROE; net income of year t deflated by book equity of year t.

GP; sales revenue of year t minus cost of goods sold of year t.

OP; adopted from Ball et al. (2015 and 2016). We calculate OP using the balance sheet of year t. The OP captures the pure operational performance of firm since it is free from non-operating items (e.g. leverage and taxes). Variable can be defined as follows,

OP = GP

– general and administrative expenses (excluding research and development[72])

CBOP; is an AR free version of OP and it has the potential to be more informative related with the E-Rs than the book earnings. Unlike the earnings before extraordinary items and free cash flows, CBOP is free from accounts payables and interest and taxes, which are regarded as the components of the ARs. We adopt CBOP from Ball et al. (2016) and use balance sheet of year t and t-1 to calculate it. Variable can be defined as follows,

CBOP[73] = OP

- Δ accounts receivable

- Δ inventory

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[72] OP include research and administrative expenditures. The general and administrative expenses are actual reporting numbers. Although research and development (R&D) expenditures reported as they are incurred, they represent expenses to generate future revenue. Therefore, not reducing R&D expenditure from the current revenue is expected to increase the predictive power of the OP (Ball et al., 2015).

[73] In the calculation of the CBOP, the data related with the changes in the prepaid expenses and the changes in the deferred revenue are missing for the period from 2006 to 2012. These items are started to get reported since 2013 in Turkey. Therefore, we follow Ball et al. (2016) and replace missing data with zero. It is important to add that the magnitude of these implied items is tiny.

- Δ prepaid expenses

+ Δ deferred revenue

+ Δ trade accounts payable

+ Δ Accrued expenses

where, Δ represents unit change from year t-1 to year t.

ARs; we adopt ARs from Sloan (1996)[74]. Hribar and Collins (2002) show that the ARs which are calculated using balance sheet create errors in the estimations. According to them, this is because of events like mergers and acquisitions. Ball et al. (2016) use both balance sheet and income statement to calculate ARs and obtain similar results. Therefore, we use balance sheet approach. We replace missing values with zero following Ball et al. (2016) and use balance sheets of year t and t-1 in the calculation of ARs. Variable can be defined as follows,

ARs = (Δ current assets - Δ cash and cash equivalents)

- (Δ current liabilities

- Δ debt included in current liabilities

- Δ income taxes payable)

- Depreciation and amortization

where, Δ represents unit change from year t-1 to year t.

Profitability measures are either deflated by the book equity or book assets in the asset pricing literature. For example, FF (2015) deflate OP (revenues reduced by cost of goods sold, selling, general and administrative expenses and interest expenses) by the book equity. Analogously, FF (2006) deflate earnings by book equity. In contrast, Novy-Marx (2013) scale GP by the book assets while earnings and free cash flows by the book equity. Ball et al. (2015) deflate OP by the total book assets. In addition, Ball et al. (2016) deflate ARs, OP, and CBOP by the total book assets. Different measures are scaled by using different deflators depending on various underlying reasons. According to Ball et al. (2015), using a consistent deflator is crucial when comparing whether different

[74] We deflate ARs by fiscal year ending total book assets. The aim is to adopt a consistent deflator among different profitability measures. See Ball et al. (2015) for a nice discussion on the importance of the consistency of deflators among horse race variables.

variables are more informative about the E-Rs. In the face of this critique, except for the ROE, we deflate all the profitability variables by the book value of total assets of year t.

3.3.2. Investment Variables

We use three different variables to proxy the corporate investment effect; such as, the AG of year t-1, AG of the current year and IG of the current year. Calculations are as follows,

Asset growth 2 (AG2); we adopt AG2 from Cooper et al. (2008). They argue that the total AG can capture the entire change in the investment (i.e. assets) and financing (i.e. liabilities) activities.

AG2 = (total assets of t-1 - total assets of t-2) / Total assets t-2

Asset growth 1 (AG1); is previous year's AG.

AG1 = (total assets of t - total assets of t-1) / Total assets t-1

IG; We adopt IG from Xing (2008). He represents the IG by using year by year changes in the capital expenditures. We use changes in the book value of property, plant, and equipment (PPE) from year t-1 to year t. Variable can be defined as follows,

INV = (PPE t – PPE t-1) / PPE t-1

Where, PPE stands for book value of property, plant and equipment.

3.3.3. Prior Performance Variables

We use two different variables to measure the short to medium term prior performances of sample firms. Calculations are as follows,

Momentum 6 (M6,1); is the simple summation of monthly stock returns from month t-6 to t-1. We left the most recent month out of the calculation following FF (2008 and 2012).

Momentum 12 (M12,1) is the simple summation of monthly stock returns from month t-12 to t-1.

3.3.4. Other Variables

We further examine the market capitalization, i.e. size, valuation ratio, historical beta and financial leverage ratio. Calculations are as follows;

ME; represents the total market value of firms (shares outstanding times market price of equity at the last day of trading of each June) following FF (1993 and 2015). We use ME to proxy firm size.

B/M; is the ratio of book equity, that is the book value of equity at fiscal year ending in year t, to the M, that is the ME of equity at December t-1. We follow FF (1993 and 2015) to calculate B/M ratio.

D/E; is the ratio of the total book debt at December t to total book equity at December t. Variable proxy the financial leverage.

β; we regress historical monthly excess returns on *BIST-100* index against historical excess returns on each stock (we use at least eighteen months of the past four years to estimate βs).

3.4. PORTFOLIO SORTS

Initially, we investigate the relationship between E-Rs and fundamental variables such as ME, B/M, ROA, ROE, OP, CBOP, ARs, M6,1, M12,1, AG1, AG2, IG, D/E and β. To this end, we use portfolio sorts analysis from July 2006 to December 2015. We describe the reasons for our choice on portfolio analysis over the cross-sectional regression in *Section 3.4.1*.

3.4.1. Sorts Over Cross-Sectional Regressions

We prefer sorts analysis for several reasons, such as; first, univariate portfolio sorts enable the examination of underlying fundamental portfolio characteristics. This is important since the theory behind rational pricing equations relies on underlying fundamental reasons. A cross-sectional regressions methodology is silent on this issue.

Second, BIST is a developing market with volatile stock characteristics, and FM (1973) procedure is highly sensitive to outliers. Therefore, the FM methodology would lead to the loss of significant amount of data, and the number of sample is already restricted.

Third, FM (1973) weight stocks with different market capitalization equally. However, in real-life markets, investors usually consider V-W investment strategies. In addition, the sample includes stocks from national, second national, watch-list and new economy markets. Stocks from these markets traded less and can have bouncing returns. Therefore, using V-W portfolio sorts is more appropriate.

Finally, as Rowenhorst (1999: 1446) stress out, the cross-sectional regression of FM (1973) does not constraint portfolio weights to be positive.

3.4.2. The Market Portfolio

From July 2006 to December 2015, at the end of each June we allocate all the stocks to a V-W portfolio, calculate its monthly excess returns[75] and rebalance it annually. We consider the excess returns on this portfolio to proxy the market portfolio in pricing tests.

3.4.3. Sorts on Size

We rank all the stocks at the end of each June, from 2006 to December 2015, independently based on their ME values and allocate them into five different investment portfolios. Following Banz and Breen (1986) and FF (1992) we lag the accounting information by six months to avoid the look ahead bias and then match them with monthly returns. We calculate the monthly V-W excess returns on these portfolios and rebalance them annually at the end of each June[76]. Additionally, we perform zero-investment

[75] We replicate same portfolio for the E-W investment strategy and provide descriptive statistics in Appendix 5.
[76] We replicate all the analysis for an E-W investment strategy. The results are in Appendix.

portfolio for the ME variable, representing the monthly difference between the returns on a portfolio consisting of small stocks and the returns of a portfolio consisting of the big stocks.

The breakpoint calculation for the ME adopt the 20th, 40th, 60th and 80th percentiles from the end of June ME of the entire BIST national market[77]. The calculation of ME breakpoints includes financials and negative equity stocks, whereas the empirical analysis excludes them. Additionally, the breakpoint calculation excludes watch-list, new economy and second national markets to avoid the overconcentration of tiny stocks in extreme decile portfolios[78]. However, we consider these stocks for the empirical analysis.

In addition, to examine the underlying drivers of pricing anomalies, we investigate portfolio characteristics such as the averages of ME, B/M, β, D/E, CBOP, ARs, AG2 and M6,1. The selection of these variables is not arbitrary, rather rely on our results of the correlations and portfolio analyses[79]. Except for the ME, β and M6,1, we measure these variables at December t-1, and first average them across portfolios and then across time. We rebalance these variables annually. We replicate all the analysis for E-W investment strategy and report results in Appendices 1, 2, 3 and 4, respectively.

Finally, we regress average excess returns on each portfolio against CAPM, FF3M, Q-Factor and FF5M. We provide details for factor construction in *Section 3.5*.

3.4.4. Other Sorts

We replicate the entire portfolio methodology described in *Section 3.4.3* for the other variables, namely, B/M, CBOP, ARs, M6,1, AG2, D/E and β[80]. Whereas, for the

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[77] Due to the unavailability of the data, we use averages of the end-of-year market capitalizations of years 2004-2005, 2005-2006, 2006-2007 and 2007-2008 to obtain end of June market capitalization of years 2005, 2006, 2007 and 2008, respectively.

[78] The market share of the BIST second national market increased over 2.5% by 2012; hence, we consider it for the ME breakpoint calculation following 2012. In this way, the analysis ensures that the breakpoint calculation always represents at least 98% of total BIST capitalization.

[79] The choice of variables under consideration relies on the fact that they produced larger variations in average returns compared to their relatives. Details on the univariate sorts on each variable is tabulated in Appendices 1 to 3.

[80] We replicate the same investment strategy for AG1, INV, M12-1, ROA, ROE, GP and OP and report results in Appendices 1 to 3.

breakpoint calculation of these variables we use 20th, 40th, 60th and 80th percentiles considering only the big stocks, namely, the stocks that that are above the BIST national market median ME. Our breakpoint calculation methodology aims to reduce the impact of tiny stock on the results and it is in line with those of Cakici et al. (2012) and FF (2012, 1993, 1996 and 2015).

We construct zero-cost portfolios for the other variables considering the speculations of CAPM, equation 3 and prominent empirical evidence.

3.5. FACTOR CONSTRUCTION

We follow FF (1993 and 2015) to construct our factors. Initially, at the end of each June, we divide all the stocks into two groups as big (B) and small (S), using the June ME of the BIST national market. Then we identify three B/M breakpoints among big stocks such as low (L, bottom 30%), medium (N, neutral 40%) and high (H, top 30%)[81]. Following this step, we construct six intersection portfolios: S∩L, S∩N, S∩H, B∩L, B∩N and B∩H. Starting from July, we calculate monthly V-W returns on these stocks until the next June and rebalance them annually. We follow a similar approach to construct profitability and investment factors with the only difference being that CBOP portfolios of robust (R, top 70% of big stocks sorted by CBOP), and weak (W, bottom 30% of big stocks sorted by CBOP) and AG2 portfolios of conservative (C, bottom 30% of big stocks sorted by AG2) and aggressive (A, top 30% big stocks sorted by AG2) replaced H and L portfolios.

Following FF (1993), we represent the $SMB_{B/M}$ (small minus big from B/M sorts), from the monthly difference between simple averages of three small and three big portfolios. Further, we obtain two additional size factors from the spanning portfolios sorted by CBOP and AG2 as SMB_{CBOP} and SMB_{AG2} in the same way. Ultimately, SMB factor is the simple average of these three different variations. Similarly, we construct the

[81] FF (1993, 1996 and 2015) refer this approach as the 2x3 factor construction and this methodology produces the highest factor premium among the strategies they evaluate. See FF (2015), page 6, Table 3 and page 7, Table 4. According to the authors the way factors are defined not influence the results. Therefore, we adopt the traditional approach.

HML from the monthly differences between simple averages of two high and two low B/M portfolios. We calculate factors RMW and CMA in the same way.

Panel A of Table 2 provides the details for the factor calculations. To avoid any miss-specification we repeat the factor construction by using sample breakpoints in the Panel B of Table 2. For that case, we use portfolio medians for ME to spit stocks as small and big and 30th and 70th percentiles of B/M, CBOP and AG2 on the sample stocks to split stocks as H and L, R and W and C and A, respectively.

Table 2: Details of SMB, HML, RMW and CMA Factors

Sorts composition	*Breakpoints used*	*Factors composition*
Panel A: SMB, HML, RMW and CMA constructed using market and big stocks' breakpoints		
2x3 E-W and V-W;		
ME and B/M	*ME;* BIST median	$SMB_{B/M}$ = [(1/3) x (SH – SN - SL)] – [(1/3) x (BH – BN – BL)]
ME and CBOP		SMB_{CBOP} = [(1/3) x (SR – SN - SW)] – [(1/3) x (BR – BN – BW)]
ME and AG2		SMB_{AG2} = [(1/3) x (SR – SN - SW)] – [(1/3) x (BR – BN – BW)]
		SMB = [(1/3) x ($SMB_{B/M}$ + SMB_{CBOP} + SMB_{AG2})]
	B/M; 30th and 70th percentiles among big	HML = [(1/2) x (SH - BH)] - [(1/2) x (SL - BL)]
	CBOP; 30th and 70th percentiles among big	RMW = [(1/2) x (SR - BW)] - [(1/2) x (SR - BW)]
	AG2; 30th and 70th percentiles among big	CMA = [(1/2) x (SC - BC)] - [(1/2) x (SA - BA)]
Panel B: SMB, HML, RMW and CMA constructed using within portfolio (i.e. sample) breakpoints		
2x3 E-W and V-W;		
ME and B/M	*ME;* Within portfolio median	$SMB_{B/M}$ = [(1/3) x (SH – SN - SL)] – [(1/3) x (BH – BN – BL)]
ME and CBOP		SMB_{CBOP} = [(1/3) x (SR – SN - SW)] – [(1/3) x (BR – BN – BW)]
ME and AG2		SMB_{AG2} = [(1/3) x (SR – SN - SW)] – [(1/3) x (BR – BN – BW)]
		SMB = [(1/3) x ($SMB_{B/M}$ + SMB_{CBOP} + SMB_{AG2})]
	B/M; 30th and 70th portfolio percentiles	HML = [(1/2) x (SH - BH)] - [(1/2) x (SL - BL)]
	CBOP; 30th and 70th portfolio percentiles	RMW = [(1/2) x (SR - BW)] - [(1/2) x (SR - BW)]
	AG2; 30th and 70th portfolio percentiles	CMA = [(1/2) x (SC - BC)] - [(1/2) x (SA - BA)]

Note: Panel A report details related with the factors that we construct from ME and B/M, ME and CBOP and ME and AG2. Initially, we split stocks using the June median ME of the BIST national market (by considering also the negative equity firms) (following 2012 second national market also included due to its increased market share) as small (S) and big (B). Then we calculate the 30th and 70th breakpoints for the B/M, CBOP and AG2 using only the big stocks and label them as low (L) vs. high (H), robust (R) vs. weak (W) and conservative (C) vs. aggressive (A), respectively. Mid-40 percent are neutrals (N) for each case. Then we form Intersection portfolios of two size groups and three B/M, CBOP and AG2 groups, hold these portfolios for the next twelve months and rebalance them annually at the end of each June. Panel B repeats the same procedures, however, adopts sample breakpoints instead.

3.6. MODEL PERFORMANCE TESTS

In this thesis, we are motivated from the guidance of CAPM, the valuation equation of FF (2006), the q-theory of investment and prominent empirical evidence and test the performances of CAPM, FF3M, the Q-Factor model and FF5M against related and unrelated pricing anomalies, such as ME, B/M, β, D/E, CBOP, ARs, AG2 and momentum. Pricing equations that can fully explain average stock returns must extract insignificant intercepts equal to or at least close to zero (Huberman and Kandel, 1987). Firstly, GRS test examined the joint insignificance of intercepts hypothesis. Formally, it examines whether $H_0 = \alpha_1 = \alpha_2 \ldots = \alpha_n = 0$ and excludes hedge portfolios due to the problem of perfect multicollinearity.

The GRS test does not tell which model is better. It only tests the mean-variance efficiency of factors. To examine the economic significance of the models, we adopt several other test statistics from FF (2016 and 2017). First, we adopt the average absolute intercepts (A. $|\alpha_i|$). The smaller value, the better the explanatory power of the model. Second, we adopt the absolute average standard errors of intercepts (A. s (α_i)). The smaller errors, the better the model. Third, we adopt a ratio that measures the intercept dispersion, i.e., the absolute value of the intercept to the average absolute value of average excess portfolio returns minus average V-W market portfolio return (A. $|\alpha_i|$ / A. $|\bar{r}_i|$). Fourth, we adopt the squared version of the dispersion ratio (A. α_i^2/ A. $\bar{r}_i^2$). The use of the market portfolio as a reference point is appropriate since according to FF (2016), it consists entirely of stocks that the thesis considers. Smaller values, specifically values lower than 1, are good news, indicating that the model can deflate excess returns. Fifth, we adopt a ratio that measures the fraction of dispersion, which models attribute to the sampling errors. This is the ratio of the squared average value of standard errors of the intercepts to the average value of squared alphas (A. s^2 (α_i) / A. α_i^2). A larger value is good news. Finally, we adopt the average adjusted coefficient of determination (A. (R^2)) to measure the regression fit.

3.7. ROBUSTNESS TESTS

We apply several robustness checks to justify our methodology under two categories such as (i) robustness tests related with the sorts and variables and (ii) robustness tests related with the factors and their calculations.

3.7.1. Robustness Tests Related with Sorts and Variables

First, studies investigating the emerging markets constructs E-W portfolios and factors. We replicate returns on entire sorts for E-W investment strategies (see Appendices 1, 2, 3 and 4). However, in the pricing test we prefer V-W strategies which is more theoretical. Second, our choice on profitability, investment and momentum proxies depends on the amount of variation which they have caused in the average returns, and not on arbitrary judgement. Third, our breakpoint procedure is to minimize the effects of small and tiny stocks on our results. FF (2008) show that anomalies may be unique to the micro-capitalization stocks (stocks that are below the 20^{th} percentile of NYSE market equity). They analyze size, value, profitability, ARs, momentum and AG anomalies within micro-capitalization group. Our study has similarities with that of FF (2008), according to the anomaly categories. Whereas, it is not possible to adopt their methodology due to restricted sample size. However, our results are largely free from the micro-firm effects due to the breakpoint calculation methodology. Finally, we replicate all the sorts and factor analysis for two different sub-periods, 2005 to 2009 and 2010 to 2015 (see Appendices).

3.7.2. Robustness Tests Related with Factors

We construct factors with two different breakpoint calculation procedures such as (i) we use market percentiles and big stocks and (ii) we use within portfolio breakpoints considering only the sample stock. Results from factor spanning tests indicate that factors adopting the former strategy is more efficient. Additionally, we supplement this results with portfolio optimization on factors.

CHAPTER FOUR
FINDINGS

Chapter four presents the empirical results. First, we provide summary statistics and correlations related with the variables and factors. Then, we report results of portfolio analysis. Finally, we document model performance test results, spanning regressions results and factor optimization.

4.1. SUMMARY STATISTICS AND CORRELATIONS

This section describes the variable summary statistics and cross-correlations.

4.1.1. Variable Summary Statistics

Table 3 reports the mean, median, SD, 25th and 75th percentiles for the variables. According to the findings all the variables are highly volatile; such as, their SDs are at least 2 to 4 times higher than their means. Panel A of Table 3 reports summary statistics for the profitability variables. The GP has the highest mean value (0.187) since it is only adjusted by the cost of goods sold. The mean CBOP (0.046) is lower than that of the OP (0.059). The difference is approximately equal to the mean ARs (-0.015)[82]. The ROA and ROE have mean values of 0.039 and 0.031, respectively. The ROE is almost five times much more volatile (SD = 0.514) than other profitability proxies.

Panel B of Table 3 reports statistics related with the corporate investment proxies. The means of AG1, AG2 and IG are 0.131, 0.156 and 0.228, respectively. The medians of AG1 and AG2 are equal (0.087). However, the median of IG is far lower, 0.027, and analogously its SD is considerably larger than those of both AG1 and AG2.

Panel C of Table 3 reports prior returns statistics. Prior twelve months return is only 5 percent higher than the prior six month returns, whereas, both are highly volatile.

[82] Negative value of ARs is due to the adjustment for the depreciation and amortization.

Panel D of Table 3 results indicate that the size variable is highly volatile. Average June ME is approximately 614 million U.S. Dollars. Whereas, the median of ME is 95 million U.S. Dollars with a SD of 1.7 billion. The variability of B/M ratio is also high; such as, its SD (0.709) is almost as large as its median (0.749). In addition, the SD of the D/E ratio is 2.190. Lastly, mean and median of β is approximately 1 with a SD of 0.319.

Variables under consideration is highly volatile with large outliers. These findings justify our choice of the sort analysis over cross-sectional regression since the V-W sorts analysis does not sensitive to the outliers like that of the FM (1973) regression.

Table 3: Descriptive Statistics for Variables

Variables	*Mean*	*Median*	*Standard Deviation*	*Percentile* *25th*	*75th*
		Panel A: Profitability variables			
GP	0.187	0.169	0.135	0.095	0.251
OP	0.059	0.054	0.089	0.006	0.099
CBOP	0.046	0.040	0.109	-0.017	0.102
ARs	-0.015	-0.014	0.104	-0.061	0.036
ROA	0.039	0.037	0.100	0.000	0.085
ROE	0.031	0.076	0.514	0.002	0.152
		Panel B: Asset growth variables			
AG1	0.131	0.087	0.270	0.003	0.206
AG2	0.156	0.087	0.658	-0.000	0.216
IG	0.228	0.027	1.944	-0.043	0.166
		Panel C: Momentum variables			
M6,1	13.574	8.644	40.644	-10.466	30.385
M12,1	18.569	10.961	42.028	-12.576	42.028
		Panel D: Other variables			
ME	613,873	94,870	1,744,396	30,820	341,109
B/M	0.913	0.749	0.709	0.463	1.138
D/E	1.306	0.759	2.190	0.348	1.623
β	1.011	1.013	0.319	0.820	1.191

Note: Table 3 reports the mean, median, SD, 25th and 75th percentiles for the variables. Panel A reports statistics related with the profitability proxies. GP represents revenues minus cost of goods sold. OP is GP minus selling, general and administrative expenses net of research and development expenditures of t-1. CBOP is OP minus changes in t-2 to t-1 [accounts receivable, inventory and prepaid expenses] plus changes in t-2 to t-1 [deferred revenues, accounts payable, accrued expenses]. ARs is changes in t-2 to t-1 current assets minus changes in t-2 to t-1 [cash, current liabilities, current debt, and income taxes payable] minus year t-1 depreciation. ROA is net income of t-1. We deflate all by total book assets of t-1. ROE is net income of t-1 deflated by total book equity of t-1. Panel B reports AG variables. AG1 is percent change in year t-2 total book assets to year t-1 total book assets. AG2 is the percent change in year t-3 total book assets to year t-2 total book assets. IG is percent change in the value of plant, equipment and building from year t-2 to year t-1. Panel C reports prior return performance. Momentum variables of M6,1 and M12,1 represents simple summations of monthly returns of preceding 12 and 6 months excluding the most recent month. Finally, in Panel D we report summary statistics for other variables. ME represents market value of outstanding shares at the final trading day of June t and reported in millions. B/M ratio is end of reporting year book equity deflated by December t-1 market equity. Market β represent the coefficients of regressions on excess monthly returns on individual stocks against the excess monthly returns on the *BIST-100* index (uses at least eighteen of forty-eight months prior).

4.1.2. Variable Correlations

Table 4 reports correlation coefficients between the variables. Several important patterns emerge. First, all the profitability variables are in a strong positive relationship among each other. Similarly, there is a positive relationship between ARs and earnings-based profitability measures such as GP, OP, ROA and ROE. However, the correlation coefficient between CBOP and ARs is negative and strong (-0.40; $p< 0.01$). This result demonstrates that the companies reporting high levels of ARs appears to have higher profits, whereas, they are less profitable based on cash.

Second, consistent with the speculations of equation 3, all the profitability variables, except ARs, are positively correlated with ME and negatively correlated with B/M. Therefore, profits effect the market value positively but ARs effect the market value negatively.

Third, correlation coefficients among investment proxies and ME and investment proxies and B/M are weak in contrast to equation 3.

Fourth, consistent with the speculations of equation 3, we observe a negative correlation coefficient between ME and B/M (-0.18; $p < 0.01$).

Fifth, the relationships between profitability and investment variables are weak. Yet, ARs and AG1 is in a positive relationship (0.22; $p < 0.01$) which is not a surprise, since AR is a component of corporate investment[83].

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[83] See Fairfield et al. (2003) for details on this issue.

4.1.3. Factor Summary Statistics

We examine the V-W $r_m - r_f$, SMB, HML, RMW and CMA factors. We use CBOP and AG2 in constructing factors RMW and CMA respectively since these variables produces larger variations in the average returns compared to others[84]. Table 5 reports findings[85].

The results in Panel A of Table 5 indicate that all the factor premiums are insignificant. The average monthly equity premium is low (0.15 percent) and highly volatile. The size premium is 8 basis points higher than the market premium. The value premium is economically high (0.76), but insignificant (t = 1.12).

We construct same factors using sample breakpoints and present the results in Panel B of Table 5. The SMB premium stayed the same, whereas, the HML and RMW premiums decreased at least 20 to 30 basis points, respectively. However, CMA premium increased 18 basis points. Whereas, all the premiums are still insignificant.

The results in Appendix 5 indicates that the bulk of the equity premium in BIST experienced from 2006 to 2009. From 2010 to 2015, the market premium is negative. The RMW returns moves in the opposite direction with the market returns. From 2006 to 2009, all the variations of RMW lost, in average about -0.80 to -1.17 percent. Whereas, RMW earns (0.65 percent; $p < 0.05$) significant premiums from 2010 to 2015. Opposite is true for the SMB and CMA factors.

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84 Evidence from the U.S. is also consistent, the CBOP based profitability factor of Ball et el. (2016) produces larger variations compared to the earnings based profitability measure of FF (2016). And the result related with AG2 is consistent with Cooper et al. (2008) and others. See, Appendices 1 to 3.

85 See Appendix 5 for descriptive statistics on other variations of factors.

Table 4: Correlations Between Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
							Profitability variables								
(1) GP	1														
(2) OP	0.60***	1													
(3) CBOP	0.39***	0.63***	1												
(4) ARs	0.06**	0.12***	-0.40***	1											
(5) ROA	0.40***	0.67***	0.39***	0.17***	1										
(6) ROE	0.14***	0.30***	0.15***	0.11***	0.48***	1									
							Asset growth variables								
(7) AG1	0.03	0.14***	-0.05**	0.22***	0.20***	0.10***	1								
(8) AG2	-0.02	0.02	0.00	0.03	0.01	0.02	0.01	1							
(9) IG	-0.06**	-0.03	-0.03	0.08***	0.02	0.01	0.13***	0.00	1						
							Momentum variables								
(10) M6,1	0.06**	0.09***	0.08***	-0.02	0.02	0.03	0.05**	-0.02	-0.04	1					
(11) M12,1	0.08***	0.12***	0.11***	-0.05**	0.10***	0.08***	0.04	-0.03	-0.05**	0.69***	1				
							Other variables								
(12) ME	0.16***	0.22***	0.18***	-0.07***	0.17***	0.09***	0.05**	0.00	-0.01	0.00	0.03	1			
(13) B/M	-0.24***	-0.20***	-0.11***	-0.02	-0.20***	-0.05**	-0.08***	-0.02	-0.01	0.18***	-0.11***	-0.18***	1		
(14) D/E	-0.01	-0.15***	-0.09***	-0.04**	-0.31***	-0.73***	0.04**	-0.01	-0.01	-0.04**	-0.08***	-0.01	-0.10***	1	
(15) β	0.00	-0.03	0.00	-0.03	-0.05**	-0.01	-0.02	-0.07***	-0.01	0.05**	0.04	-0.04	0.13***	0.05**	1

Note: Table presents variable correlation coefficients. Profitability variables, AG variables and B/M and D/E represents December t-1 values. We measure rest of the variables at the end of each June. We provide description of variables in Table 3. Average number of firms is 160, ranging from 133 in 2006 and 204 in 2015. Our sample starts in July 2006 and ends in December 2015. *** and ** indicates statistical significance at the 1% and 5% levels, respectively.

Table 5: Average Factors Returns

Panel A: Mean returns, t-stat. and SD of factors using market and big stock breakpoints

2006 to 2015

	V-W returns on 2x3 factors				
	$R_M - R_f$	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.15	0.23	0.76	0.04	-0.06
t-stat.	0.16	0.47	1.12	0.09	-0.14
SD	8.74	5.15	7.58	4.48	4.18

Panel B: Mean returns, t-stat. and SD of factors using within portfolio breakpoints

	V-W returns on 2x3 factors				
	$R_M - R_f$	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.38	0.24	0.56	-0.26	0.12
t-stat.	0.37	0.46	0.96	-0.58	0.27
SD	9.48	5.26	6.98	4.82	4.80

Note: From July 2006 to 2015, we construct V-W factors that mimic market, size, value, profitability and investment effects. The market portfolio represents average monthly returns on sample stocks each year. We provide variable descriptions in Table 3. Panel A reports the average returns (mean), t-statistics (hereafter t-stat.) and SD on returns of the factors that uses market breakpoints. The calculation of market median ME considers all the stocks listed in the BIST national market (following 2012 second national market also included due to its increased market share) at the end of each June. We also consider negative equity stocks and financials for the ME breakpoint calculation. Factors of HML, RMW and CMA uses December t-1 B/M, CBOP, and AG2 and splits stocks at 30th and 70th percentiles using only the big (B) stocks. Factors compose of the intersection of two size groups and three B/M or CBOP or AG2 groups. Panel B replicates the same analysis for factors that uses sample breakpoints. We detail factor calculations in Table 2.

4.1.4. Factor Correlations

Panel A of Table 6 reports correlation coefficients between V-W factor returns which uses market and big stocks' breakpoints[86]. According to the results the relationships between the market portfolio returns and SMB returns and between the market portfolio returns and HML returns are negligible. In addition, the correlation coefficient between market returns and RMW returns is -0.38. Similarly, the SMB and HML returns move in the opposite direction. Same is true for SMB and RMW and SMB and CMA returns. The relationship between SMB and CMA is surprising since the correlation between the ME and AG2 is negligible (see Table 4). In contrast, the correlation coefficient between the

[86] We investigate same factors with E-W returns. Results are in Appendix 6.

returns of HML and RMW and HML and CMA are positive and significant. This is also surprising since the correlation between AG2 and B/M is negligible. Finally, there is a positive relationship between RMW and CMA, indicating that the returns of profit firms tend to move in the same direction as those of firms that invest conservatively.

Panel B of Table 6 results indicate that the correlational relationships are virtually the same among factors regardless of the breakpoint calculation methodology.

Table 6: Correlations Between Factors

Panel A: Correlations between factors constructed based on market and big stocks' breakpoints

	V-W 2x3 factors				
	$R_M - r_f$	*SMB*	*HML*	*RMW*	*CMA*
$R_M - r_f$	1.00	0.03	-0.01	-0.38***	0.09
SMB	0.03	1.00	-0.59***	-0.39***	-0.35***
HML	-0.01	-0.59***	1.00	0.34***	0.44***
RMW	-0.38***	-0.39***	0.34***	1.00	0.25***
CMA	0.09	-0.35***	0.44***	0.25***	1.00

Panel B: Correlations between factors constructed based on within portfolio breakpoints

	V-W 2x3 factors				
	$R_M - r_f$	*SMB*	*HML*	*RMW*	*CMA*
$R_M - r_f$	1.00	0.04	-0.02	-0.29***	0.01
SMB	0.04	1.00	-0.61***	-0.38***	-0.37***
HML	-0.02	-0.61***	1.00	0.30***	0.46***
RMW	-0.29***	-0.38***	0.30***	1.00	0.35***
CMA	0.01	-0.37***	0.46***	0.35***	1.00

Note: Panel A reports correlations between V-W factors that we construct using market breakpoints. Panel B reports correlations between factors that we construct using sample breakpoints. We provide details for the factor construction in Table 2. *** indicates statistical significance at 1% level.

4.2. UNIVARIATE PORTFOLIO SORTS

This section presents the average excess returns for the portfolios sorted by variables namely β, ME, B/M, D/E, CBOP, ARs, AG2 and M6,1. Additionally, the tables report the alpha estimates and adjusted R^2 values from the regressions of CAPM, FF3M, the q-factor and FF5M. Standard errors reported following the procedure of Newey and West (1987). Coefficient loadings for each model are in Appendices 11 to 18. We start the factor and portfolio construction in July 2006 and end it in December 2015 (hereafter 2006 to 2015).

4.2.1. Portfolios Sorted by Beta

Panel A of Table 7 indicates an average loss of -0.38 percent on a portfolio consisting of the lowest β stocks. Consistent with the speculations of CAPM, average excess returns increase from p1 to p4 and then the relationship becomes flat. The monthly average excess return on p5 is 0.81 percent. This difference yields a monthly premium of 1.20% (t = 1.91) on a zero-cost high beta portfolio. This premium remains significant against CAPM and Q-Factor model. This is partially due to the absence of the HML factor since returns on the zero-investment high β portfolio behaves like those of value firms. Analogously, FF3M and FF5M decreases the premium on p5, at least 24 to 30 basis points. Additionally, CAPM and Q-Factor face difficulty against p5 returns, which behave like those of value firms with weak profits. The coefficient estimates in Appendix 11 indicate that the β loadings of p1 are lower than those of p5. In addition, p5 has positive exposure to HML and negative exposure to RMW. The negative RMW coefficient justifies findings in Panel B of Table 5, whereas HML coefficient is surprising.

Panel B of Table 7 reports the portfolio characteristic. The results indicate that the p5 has higher D/E ratio than p1. Additionally, p5 tend to be small with high B/M ratio and low investment compared to p1.

Table 7: Excess Returns on Market Beta Sorts

Panel A: Return characteristics and model performances on β sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	32	12.4	-0.38	-0.52*	0.85	-0.44	0.85	-0.52	0.85	-0.45	0.85
			(-0.40)	(-1.67)		(-1.33)		(-1.59)		(-1.35)	
p2	32	10.7	-0.21	-0.33	0.80	-0.29	0.79	-0.35	0.81	-0.34	0.81
			(-0.26)	(-0.87)		(-0.77)		(-0.94)		(-0.92)	
p3	34	11.7	0.10	-0.06	0.85	-0.14	0.85	-0.13	0.86	-0.13	0.86
			(0.08)	(-0.14)		(-0.33)		(-0.32)		(-0.32)	
p4	31	10.3	0.83	0.67	0.87	0.55	0.88	0.69*	0.88	0.56	0.89
			(0.75)	(1.60)		(1.48)		(1.90)		(1.75)	
p5	32	11.1	0.81	0.64*	0.87	0.49	0.88	0.67*	0.88	0.53	0.88
			(0.68)	(1.73)		(1.32)		(1.76)		(1.47)	
Hedge			1.20*	1.16**	0.07	0.92	0.11	1.20*	0.09	0.98	0.12
p5-p1			(1.91)	(1.98)		(1.51)		(1.93)		(1.60)	

Panel B: Portfolio characteristics

	ME_{USD}	*B/M*	*β*	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	0.97	0.74	0.59	1.11	0.05	-0.01	0.25	16.7
p2	0.69	0.86	0.86	1.26	0.05	-0.02	0.14	12.9
p3	0.47	0.98	1.02	1.20	0.05	-0.02	0.12	13.3
p4	0.54	0.96	1.16	1.33	0.05	-0.01	0.13	15.5
p5	0.56	0.99	1.44	1.44	0.05	-0.02	0.13	16.5

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using June t β values from 2006 to 2015 and we determine the breakpoints of β as the 20^{th}, 40^{th},60^{th} and 80^{th} percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012, the second national market is also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors which use market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3. * indicates statistical significance at the 10% level.

4.2.2. Portfolios Sorted by Market Capitalization

Panel A of Table 8 indicates higher average returns for the portfolio composed of small stocks than for the portfolio composed of big stocks. Accordingly, an investment strategy that finances a portfolio of small stocks with a portfolio of big stocks yields 0.90% (t = 1.18) of a monthly premium. This premium is economically large but not statistically significant. All the models justify this conclusion. The insignificance for this premium is partially attributable to the high variability of returns. In contrast, FF3M produces the lowest intercept with the lowest t-stat. against this hedge portfolio and against the portfolio consisting of the smallest stocks (p1). The, CAPM intercept exactly meets the size premium since returns on the hedge portfolio are not exposed to β. The coefficient loadings in Appendix 12 indicate that p1 has positive yet less exposure to β compared to p5. Therefore, it is not the β that underlies this size premium. Additionally, p1 has positive exposures to SMB, HML and CMA, indicating that the returns on small firms behave like those of value firms that invest conservatively.

The results in Panel B of Table 6 indicate that small firms have a high D/E ratio and low profits compared to big. Additionally, the zero-investment portfolio of small firms is not exposed to CAPM.

Table 8: Excess Returns on Market Capitalization Sorts

Panel A: Return characteristics and model performances on ME sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	21	14.3	0.98	0.83	0.62	0.25	0.80	0.62	0.79	0.32	0.82
			(0.83)	(1.15)		(0.56)		(1.35)		(0.79)	
p2	38	11.3	0.22	0.07	0.82	-0.38*	0.96	-0.09	0.93	-0.37*	0.96
			(0.21)	(0.17)		(-1.82)		(-0.35)		(-1.78)	
p3	36	12.4	0.26	0.12	0.78	-0.14	0.95	-0.04	0.95	-0.13	0.95
			(0.26)	(0.26)		(-0.62)		(-0.18)		(0.63)	
p4	34	8.64	0.20	0.05	0.86	-0.21	0.90	-0.00	0.89	-0.19	0.91
			(0.19)	(0.13)		(-0.70)		(-0.00)		(-0.61)	
p5	31	8.95	0.08	-0.07	0.95	0.01	0.95	-0.05	0.95	0.01	0.95
			(0.09)	(-0.57)		(0.05)		(-0.40)		(0.08)	
Hedge			0.90	0.90	-0.01	0.25	0.48	0.67	0.44	0.31	0.52
p1-p5			(1.18)	(1.18)		(0.55)		(1.46)		(0.77)	

Panel B: Portfolio characteristics

	ME_{USD}	*B/M*	*β*	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	0.01	1.03	0.98	1.87	0.01	-0.03	0.13	2.51
p2	0.03	1.11	1.01	1.37	0.02	-0.00	0.17	12.8
p3	0.09	1.03	1.01	1.05	0.04	-0.01	0.14	17.6
p4	0.28	0.79	1.03	1.06	0.07	-0.02	0.14	20.0
p5	2.68	0.61	1.02	1.25	0.09	-0.03	0.17	15.7

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using end of June t ME values from 2006 to 2015 and the breakpoints of ME are determined as the 20th, 40th,60th and 80th percentiles by considering the entire stocks in the BIST national market (following 2012, the second national market is also included into size breakpoint calculations due to its increased market share). When determining the ME breakpoints, we consider the stocks with negative equity and the stocks of the financial sector companies however, they are ignored in sorts. We rebalance portfolios annually. Panel A reports excess returns, the SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that use market breakpoints. *SD* and *n* are averaged across portfolios and then across time. The numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3.

4.2.3. Portfolios Sorted by B/M Ratio

Panel A of Table 9 shows a positive monthly premium on the zero-investment value portfolio that is economically large (1.69 percent) and statistically significant (t = 2.40; $p < 0.05$). The models also justify this value premium. The alpha estimates from CAPM and q-factors meet the value premium of the hedge portfolio. This is partially due to the absence of the HML factor in these pricing equations since models with the HML factor, namely, FF3M and FF5M, can deflate this value premium more than 50 basis points but it remains significant. Additionally, each model faces difficulties against p5 returns that behave like those of small and unprofitable stocks with aggressive investment since p5 has positive exposures to HML and SMB and negative exposures to CMA and RMW. These loadings are consistent with the speculations of equation 3.

The results in Panel B of Table 9 indicate that value stocks are unprofitable compared to growth. Additionally, the zero-investment value portfolio does not have significant exposure to β.

Table 9: Excess Returns on B/M Sorts

Panel A: Return characteristics and model performances on B/M sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	23	11.0	-0.07	-0.20	0.89	-0.09	0.89	-0.21	0.89	-0.08	0.91
			(-0.09)	(-0.82)		(-0.32)		(-0.92)		(-0.31)	
p2	26	12.5	0.22	0.07	0.89	0.09	0.90	0.03	0.90	0.08	0.90
			(0.21)	(0.26)		(0.38)		(0.12)		(0.32)	
p3	27	9.9	-0.09	-0.25	0.88	-0.30	0.88	-0.27	0.88	-0.31	0.88
			(-0.08)	(-0.72)		(-0.84)		(-0.74)		(-0.87)	
p4	34	10.9	-0.25	-0.42	0.89	-0.48	0.89	-0.40	0.89	-0.46	0.89
			(-0.22)	(-1.41)		(-1.60)		(-1.34)		(-1.56)	
p5	51	11.7	1.62	1.47***	0.78	1.09**	0.85	1.48***	0.79	1.08**	0.85
			(1.47)	(2.71)		(2.34)		(2.82)		(2.59)	
Hedge			1.69**	1.67**	0.02	1.18*	0.22	1.69***	0.07	1.15**	0.34
p5-p1			(2.40)	(2.46)		(1.89)		(2.64)		(2.20)	

Panel B: Portfolio characteristics

	ME_{USD}	*B/M*	*β*	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	1.57	0.24	0.90	2.02	0.09	-0.04	0.17	14.3
p2	0.89	0.48	1.03	1.38	0.07	-0.02	0.16	14.6
p3	0.53	0.69	1.04	1.39	0.04	-0.01	0.11	12.5
p4	0.36	0.97	1.03	1.10	0.04	-0.01	0.15	15.3
p5	0.23	1.60	1.03	0.91	0.02	-0.01	0.16	16.4

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 B/M values from 2006 to 2015 and we determine the breakpoints of B/M as the 20^{th}, 40^{th},60^{th} and 80^{th} percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3. *** and ** indicates statistical significance at the 1% and 5% levels, respectively.

4.2.4. Portfolios Sorted by D/E Ratio

Panel A of Table 10 indicates a positive D/E premium on the zero-investment portfolio of high D/E stocks. The D/E premium is insignificant partly due to the high volatility of portfolio returns and partly due to the non-linear relationship between D/E and E-Rs. In contrast, all the models fail against p5 returns, which behave like those of firms with high market exposure and conservative investment since p5 has positive exposures to β and CMA. Additionally, except for CAPM, all the models inflate the premium on the hedge portfolio, both economically and statistically. According to Appendix 14, this finding is due to the negative large exposures of hedge returns to the factors HML and SMB since they behave like growth and big firms.

The Panel B of Table 10 indicates a higher average β value for the p5, portfolio with stocks that has the highest D/E ratio. In addition, p5 firms tend to be less profitable compared to p1 firms.

Table 10: Excess Returns on D/E Sorts

Panel A: Return characteristics and model performances on D/E sorts

				CAPM		FF3M		Q-Factor		FF5M	
Portfolio	n	SD	$r^{V\text{-}W}$	α	R^2	α	R^2	α	R^2	α	R^2
p1	32	13.0	0.22	0.08	0.76	-0.14	0.79	0.02	0.78	-0.11	0.79
			(0.22)	(0.17)		(-0.34)		(0.06)		(-0.26)	
p2	25	9.28	-0.43	-0.60*	0.86	-0.73***	0.88	-0.61**	0.87	-0.72***	0.88
			(-0.48)	(-1.94)		(-2.69)		(-2.04)		(-2.68)	
p3	36	10.4	-0.05	-0.19	0.90	-0.13	0.90	-0.17	0.90	-0.15	0.90
			(-0.06)	(-0.69)		(-0.47)		(-0.63)		(-0.52)	
p4	30	11.7	0.43	0.29	0.89	0.31	0.89	0.28	0.89	0.28	0.89
			(0.46)	(1.13)		(1.16)		(1.10)		(1.11)	
p5	38	12.0	0.59	0.44*	0.91	0.41*	0.91	0.45**	0.91	0.44**	0.91
			(0.56)	(1.86)		(1.75)		(2.07)		(2.00)	
Hedge			0.37	0.36	0.01	0.55	0.07	0.43	0.05	0.55	0.05
p5-p1			(0.75)	(0.74)		(1.23)		(0.94)		(1.21)	

Panel B: Portfolio characteristics

	ME_{USD}	B/M	β	D/E	CBOP	A/Rs	AG2	M6,1
p1	0.23	0.87	0.99	0.15	0.07	-0.02	0.17	14.8
p2	0.61	0.93	0.99	0.39	0.06	-0.00	0.10	17.2
p3	0.68	1.11	0.99	0.71	0.03	-0.01	0.13	14.6
p4	0.88	0.88	1.02	1.24	0.05	-0.01	0.16	16.5
p5	0.64	0.78	1.07	3.37	0.03	-0.02	0.18	13.5

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 D/E values from 2006 to 2015 and we determine the breakpoints of D/E as the 20^{th}, 40^{th},60^{th} and 80^{th} percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3. *** and ** indicates statistical significance at the 1% and 5% levels, respectively.

4.2.5. Portfolios Sorted by CBOP

According to Panel A of Table 11, the profitability effect is insignificant in BIST[87]. The relationship between CBOP and E-Rs is not linear, as equation 3 suggests. Notwithstanding, the zero-investment portfolio of profitable stocks has positive premium, but this premium is insignificant. The models justify this conclusion. The CBOP premium is higher, both economically and statistically, according to both FF3M and FF5M. This result is largely due to the negative HML exposure of the hedge portfolio. On the one hand, the results in Appendix 15 are consistent with prior findings, indicating that p5 has negative exposure to HML and positive exposures to SMB, RMW and CMA, whereas p1 has positive exposure to HML and negative exposure to RMW. Accordingly, returns on profitable stocks behave like those of small and growth firms that invest conservatively, whereas returns on unprofitable socks behave like those of value firms. Panel B of Table 11 indicates that profitable firms have lower B/M compared to unprofitable firms. This finding is consistent with the suggestions of equation 3.

[87] We also perform portfolio analysis for AR-based profitability measures, including GP, OP, ROA, and ROE. Their association with E-Rs is found to be even weaker compared to that of CBOP. See appendices.

Table 11: Excess Returns on CBOP Sorts

Panel A: Return characteristics and model performances on CBOP sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	52	13.0	0.02	-0.15	0.89	-0.35	0.91	-0.13	0.92	-0.33	0.94
			(0.01)	(-0.42)		(-1.06)		(-0.48)		(-1.19)	
p2	33	11.7	0.41	0.25	0.76	0.14	0.76	0.33	0.83	0.21	0.83
			(0.35)	(0.56)		(0.28)		(0.73)		(0.45)	
p3	25	10.2	0.27	0.10	0.89	0.15	0.88	0.13	0.88	0.15	0.88
			(0.23)	(0.28)		(0.39)		(0.34)		(0.38)	
p4	26	10.0	-0.01	-0.15	0.91	-0.14	0.91	-0.16	0.92	-0.17	0.91
			(-0.01)	(-0.60)		(-0.58)		(-0.60)		(-0.63)	
p5	25	10.3	0.29	0.16	0.86	0.20	0.86	0.09	0.90	0.19	0.90
			(0.37)	(0.57)		(0.63)		(0.41)		(0.81)	
Hedge			0.28	0.31	0.12	0.54	0.19	0.22	0.46	0.53	0.58
p5-p1			(0.46)	(0.62)		(1.05)		(0.67)		(1.43)	

Panel B: Portfolio characteristics

	ME_{USD}	*B/M*	*β*	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	0.20	1.01	1.01	1.43	-0.06	0.03	0.14	13.1
p2	0.45	1.00	1.02	1.23	0.03	-0.01	0.17	16.0
p3	0.77	0.93	1.05	1.37	0.07	-0.03	0.15	15.1
p4	0.95	0.84	1.00	1.10	0.11	-0.03	0.11	17.6
p5	1.18	0.67	0.99	1.04	0.22	-0.07	0.19	16.7

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 CBOP values from 2006 to 2015 and we determine the breakpoints of CBOP as the 20th, 40th,60th and 80th percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3.

4.2.6. Portfolios Sorted by ARs

Panel A of Table 12 suggests that the AR effect is insignificant for BIST securities. Returns on p1 are higher than those of p5. The monthly average premium on the zero-investment low AR portfolio is 0.27 percent and insignificant. The models justify the insignificance of ARs. According to the factor loadings in Appendix 16, p1 has lower market exposure compared to p5. Additionally, p1 has positive exposures to SMB, RMW and CMA, whereas p5 has negative exposure to RMW. Therefore, returns on low ARs portfolio behave like those of small, profitable firms that invest conservatively, whereas returns on high ARs firms tilt towards unprofitable firms. These results justify prior findings on the current topic; for example, firms that appear profitable based on earning are less profitable based on cash.

Table 12: Excess Returns on ARs Sorts

Panel A: Return characteristics and model performances on ARs sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	α	R^2	α	R^2	α	R^2	α	R^2
p1	34	11.5	0.21	0.06	0.89	-0.00	0.89	0.02	0.90	0.04	0.90
			(0.31)	(0.20)		(-0.01)		(0.09)		(0.13)	
p2	28	10.9	0.01	-0.14	0.89	-0.06	0.89	-0.17	0.89	-0.08	0.90
			(0.01)	(-0.45)		(-0.19)		(-0.59)		(-0.26)	
p3	31	12.8	0.43	0.26	0.89	0.18	0.89	0.28	0.89	0.17	0.89
			(0.38)	(0.80)		(0.54)		(0.85)		(0.55)	
p4	30	10.6	0.16	0.02	0.88	-0.04	0.88	0.03	0.89	-0.02	0.89
			(0.16)	(0.06)		(-0.14)		(0.10)		(-0.07)	
p5	38	10.7	-0.06	-0.21	0.82	-0.24	0.82	-0.15	0.85	-0.25	0.85
			(-0.06)	(-0.58)		(-0.64)		(-0.44)		(-0.66)	
Hedge			0.27	0.27	-0.00	0.24	-0.02	0.17	0.20	0.28	0.21
p1-p5			(0.55)	(0.56)		(0.50)		(0.43)		(0.66)	

Panel B: Portfolio characteristics

	ME_{USD}	*B/M*	β	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	1.51	0.87	1.01	1.60	0.10	-0.15	0.13	15.6
p2	1.34	0.93	1.04	1.13	0.06	-0.05	0.12	14.5
p3	1.24	0.96	1.02	1.13	0.04	-0.02	0.21	15.7
p4	0.89	0.90	1.02	1.12	0.03	0.02	0.14	13.0
p5	0.55	0.89	0.99	1.33	-0.00	0.11	0.18	15.4

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 ARs values from 2006 to 2015 and we determine the breakpoints of ARs as the 20th, 40th,60th and 80th percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as, CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3.

4.2.7. Portfolios Sorted by Asset Growth

According to Panel A of Table 13, the association between E-Rs and AG is nonlinear and weak. This finding contradicts the speculations of equation 3 and FF (2006) [88]. The model intercepts justify the insignificance of the investment effect. According to the models, excess returns on the portfolio with the lowest AG stocks are statistically significant, and this significance becomes stronger with additional factors, indicating that these factors cannot explain the price movements for the stocks with low corporate investment levels.

The Panel B of Table 13 indicates that the portfolio consisting of stocks with low investment is smaller in terms of average ME with a higher average B/M ratio compared to the portfolio consisting of stocks with high corporate investment. These findings are also inconsistent with equation 3.

Table 13: Excess Returns on Asset Growth Sorts

Panel A: Return characteristics and model performances on AG2 sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	41	12.8	0.87	0.71*	0.83	0.60	0.83	0.73***	0.89	0.73***	0.89
			(0.77)	(1.86)		(1.46)		(2.80)		(2.85)	
p2	32	10.7	-0.21	-0.37	0.89	-0.53**	0.90	-0.41	0.91	-0.49*	0.91
			(-0.20)	(-1.30)		(-2.11)		(-1.47)		(-1.69)	
p3	28	9.37	0.08	-0.05	0.86	-0.12	0.86	-0.09	0.86	-0.14	0.86
			(0.09)	(-0.19)		(-0.49)		(-0.33)		(-0.56)	
p4	28	11.6	-0.14	-0.29	0.92	-0.27	0.92	-0.29	0.92	-0.29	0.92
			(-0.15)	(-1.07)		(-0.96)		(-1.06)		(-1.01)	
p5	32	11.2	0.69	0.55*	0.87	0.47	0.88	0.56*	0.89	0.41	0.90
			(0.72)	(1.70)		(1.40)		(1.95)		(1.55)	
Hedge			0.17	0.16	0.00	0.13	-0.01	0.17	0.42	0.32	0.44
p1-p5			(0.28)	(0.27)		(0.20)		(0.41)		(0.82)	

Panel B: Portfolio characteristics-

	ME_{USD}	*B/M*	*β*	*D/E*	*CBOP*	*A/Rs*	*AG2*	*M6,1*
p1	0.40	0.97	1.04	1.27	0.04	-0.02	-0.08	14.7
p2	0.46	0.95	1.00	1.09	0.04	-0.01	0.04	18.5
p3	0.71	0.96	1.00	1.09	0.06	-0.02	0.11	13.1
p4	1.09	0.88	1.02	1.41	0.05	-0.02	0.20	16.3
p5	0.61	0.79	1.00	1.57	0.05	-0.00	0.58	11.8

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 AG2 values from 2006 to 2015 and we determine the breakpoints of AG2 as the 20th, 40th,60th and 80th percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the

[88] We also investigate the association between growth in PPE and E-Rs. The conclusion is the same. See Appendix 2.

financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as, CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parenthesis are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

4.2.8. Portfolios Sorted by Prior Returns

According to Panel A of Table 14 trading strategies that finances a portfolio of winner stocks of the prior six-month with a portfolio of loser stocks has an average monthly premium of 0.59% from 2006 to 2016. However, this premium is insignificant. The model intercepts justify that there is no momentum anomaly in the BIST. The results in Appendix 18 related with the factor loadings are interesting since β coefficients for p1 returns are larger than p5 returns. Additionally, p1 has a positive exposure to CMA and a negative exposure to RMW. However, hedge returns do not have any exposure to any of the factors, including the β. Analogously, intercepts from all the models almost match the hedge premium.

According to the Panel B of Table 14, prior winner stocks are bigger, with higher B/M ratio, lower debt, higher profitability and lower AG compared to prior loser stocks.

Table 14: Excess Returns on Prior Performances Sorts

Panel A: Return characteristics and model performances on M6,1 sorts

				CAPM		*FF3M*		*Q-Factor*		*FF5M*	
Portfolio	*n*	*SD*	$r^{V\text{-}W}$	*α*	R^2	*α*	R^2	*α*	R^2	*α*	R^2
p1	42	12.0	-0.17	-0.34	0.84	-0.42	0.84	-0.29	0.85	-0.37	0.85
			(-0.15)	(-0.81)		(-1.05)		(-0.70)		(-0.90)	
p2	32	11.0	0.49	0.36	0.82	0.30	0.83	0.28	0.83	0.28	0.83
			(0.61)	(0.87)		(0.76)		(0.71)		(0.70)	
p3	30	9.53	0.38	0.25	0.89	0.20	0.89	0.23	0.89	0.19	0.89
			(0.42)	(1.01)		(0.89)		(0.92)		(0.83)	
p4	28	10.7	0.15	-0.01	0.86	0.01	0.85	-0.02	0.85	-0.00	0.85
			(0.13)	(-0.02)		(0.03)		(-0.04)		(-0.01)	
p5	29	12.2	0.42	0.26	0.81	0.20	0.81	0.26	0.81	0.19	0.81
			(0.38)	(0.68)		(0.53)		(0.65)		(0.48)	
Hedge			0.59	0.60	-0.01	0.62	-0.01	0.55	0.00	0.57	-0.00
p5-p1			(0.92)	(0.93)		(1.01)		(0.86)		(0.89)	

Panel B: Portfolio characteristics

	ME_{USD}	B/M	β	D/E	CBOP	A/Rs	AG2	M6,1
p1	0.47	0.81	1.00	1.66	0.02	-0.01	0.15	-17.5
p2	0.77	0.91	1.01	1.08	0.05	-0.02	0.14	2.27
p3	0.76	0.95	1.02	1.12	0.05	-0.01	0.19	14.6
p4	0.74	0.90	1.02	1.24	0.06	-0.02	0.16	30.0
p5	0.59	0.98	1.01	1.25	0.05	-0.01	0.13	63.5

Note: We form V-W ($r^{V\text{-}W}$) portfolios by using December t-1 prior six month returns (M6,1) values from 2006 to 2015 and we determine the breakpoints of M6,1 as the 20th, 40th,60th and 80th percentiles among the big stocks (stocks that are above the BIST nation market capitalization median), (following 2012 second national market also included into size breakpoint calculations due to its increased market share). While determining median ME, we consider the stocks with negative equity and the stocks of the financial sector companies however, they we ignore them in sorts. We rebalance portfolios annually. Panel A reports excess returns, SD and the average number of stocks (n) of the decile portfolios and the return of the hedge portfolios. Additionally, it reports alphas and R^2 of the models such as CAPM, FF3M, the q-factor and FF5M. Models uses V-W factors that uses market breakpoints. *SD* and *n* are averaged across portfolios and then across time. Numbers in parentheses are t-stat. adjusted according to Newey and West (1987). Panel B reports the portfolio characteristic variables, which are averaged across portfolios and then across time. The details on the calculation of the factors are given in Table 2 and the calculation of the variables are given in Table 3.

4.3. MODEL PERFORMANCE STATISTICS

In this section we summarize the performances of CAPM, FF3M, q-factor model and FF5M against the returns on portfolios sorted by β, ME, B/M, D/E, CBOP, ARs, AG2, and M6,1. We are motivated from the CAPM theory, valuation equation of FF (2006), q-theory of investment and prominent empirical evidences in choosing models and anomalies. Pricing equations that can fully explain average stock returns must extract insignificant intercepts equal to or close to zero (Huberman and Kandel, 1987). Our current effort is not to unveil an equation that can fully describe the average returns, rather to assess which model performs the best, both practically and economically. To this end, we adopt GRS[89] test and several statistics from FF (2016 and 2017). For details refer to *Section 3.6*. We provide results in Table 15.

[89] We exclude hedge portfolio returns for the GRS test. This is to avoid the perfect multicollinearity problem.

Columns 1 and 2 of Table 15 present the GRS test results and associated probabilities, respectively. The hypothesis that all the intercepts are jointly zero can be rejected for the portfolios sorted by B/M because, all the models face difficulty in explaining returns on the highest B/M portfolio. Additionally, the hypothesis can also be rejected for the CAPM and Q-Factor equations against portfolios sorted by AG2 since these models face difficulty in explaining returns on portfolios incorporating the lowest and highest AG2 stocks. For the rest of the cases, the GRS probabilities are higher than the 10% level. However, this result is not due to the mean-variance efficiency of factors. Rather, the variation in returns related to ME, β, D/E, CBOP, ARs and M6,1 is not anomalous according to the models because the statistical significance of these patterns is not that pronounced to cause any problems for the models in the GRS test.

The GRS test does not tell which model is better. It only tests the mean-variance efficiency of given factors. To examine the economic significance of the modes, we adopt several other statistics. Several important patterns emerge. First, according to Column 8 of Table 15, all the variation in portfolios sorted by ME, CBOP, ARs, and M6,1 is due to sampling errors since the ratio of A. $s^2(\alpha_i)$ / A. α_i^2 is larger than 1 for these sorts; the intercept estimation errors are larger than the intercept estimates. Second, according to the A.$|\alpha_i|$, performance of FF3M is better than those of CAPM and q-factor in three out of four cases (B/M, β and AG2). In addition, the performance of FF3M is comparable to or better than that of FF5M in all four cases. For example, FF3M produces an average intercept at least 0.01 to 0.14 points lower compared to those of the CAPM and q-factor. Third, the performance of FF5M is better than those of q-factor and CAPM in only two out of four cases (B/M and β). FF5M produces an average intercept at least 0.10 to 0.15 points lower compared to those of the CAPM and q-factor. Fourth, according to the dispersion of model intercepts relative to the dispersion of portfolio excess returns, only FF3M and FF5M can deflate excess returns on portfolios sorted by B/M and β. The performances of the models are indistinguishably close. For the other cases, the dispersion ratios are greater than one, indicating that the average monthly returns according to the models for the portfolios sorted by D/E, CBOP, ARs, AG2 and M6,1 are even larger than the portfolios excess returns. Finally, Column 8 of Table 14 indicates that FF3M attributes a larger fraction of

B/M and β related alpha dispersions to the sampling errors compared to FF5M, and, the differences are at least 6 to 8 basis points.

Consequently, results related with the model performance statistics indicate that the factors RMW and CMA are unsuccessful in improving the pricing performance of the FF3M. Whereas, factors SMB and HML significantly improves the performance of CAPM.

Table 15: Model Performance Statistics

Models	*GRS*	*p(GRS)*	$A. \lvert\alpha_i\rvert$	$A. s(\alpha_i)$	$\frac{A. \lvert\alpha_i\rvert}{A. \lvert\bar{r}_i\rvert}$	$\frac{A. \alpha_i^2}{A. \bar{r}_i^2}$	$\frac{A. s^2(\alpha_i)}{A. \alpha_i^2}$	$A. (R^2)$
β portfolios								
CAPM	1.44	0.204	0.56	0.42	1.02	1.03	0.54	0.73
FF3M	1.11	0.359	0.47	0.42	0.85	0.72	0.77	0.73
Q-Factor	1.82	0.101	0.59	0.41	1.07	1.14	0.48	0.73
FF5M	1.45	0.201	0.50	0.40	0.90	0.80	0.65	0.74
Size portfolios								
CAPM	0.47	0.833	0.34	0.48	1.08	1.17	1.97	0.67
FF3M	1.17	0.329	0.20	0.29	0.65	0.42	2.04	0.84
Q-Factor	0.46	0.834	0.24	0.33	0.77	0.59	1.83	0.83
FF5M	1.12	0.356	0.22	0.28	0.70	0.49	1.56	0.85
B/M portfolios								
CAPM	2.61**	0.021	0.68	0.40	1.03	1.07	0.34	0.73
FF3M	1.96*	0.077	0.54	0.38	0.82	0.68	0.49	0.77
Q-Factor	2.59**	0.022	0.68	0.38	1.04	1.07	0.32	0.74
FF5M	1.97*	0.076	0.56	0.35	0.85	0.72	0.39	0.79
D/E portfolios								
CAPM	1.49	0.188	0.32	0.34	1.06	1.13	1.09	0.72
FF3M	1.59	0.156	0.38	0.32	1.25	1.57	0.71	0.74
Q-Factor	1.51	0.182	0.33	0.32	1.08	1.18	0.94	0.73
FF5M	1.59	0.156	0.37	0.31	1.24	1.54	0.70	0.74
CBOP portfolios								
CAPM	0.32	0.925	0.19	0.36	1.19	1.42	3.84	0.74
FF3M	0.47	0.830	0.25	0.38	1.62	2.62	2.23	0.75
Q-Factor	0.31	0.929	0.18	0.32	1.14	1.29	2.88	0.81
FF5M	0.61	0.722	0.26	0.33	1.68	2.82	1.62	0.84
ARs portfolios								
CAPM	0.22	0.971	0.16	0.34	1.18	1.38	4.54	0.73
FF3M	0.13	0.992	0.13	0.34	0.93	0.86	7.37	0.73
Q-Factor	0.20	0.977	0.14	0.31	1.00	1.00	2.29	0.77
FF5M	0.13	0.992	0.14	0.32	1.01	1.03	5.40	0.77
AG2 portfolios								
CAPM	1.95*	0.078	0.36	0.36	0.99	0.98	1.00	0.73
FF3M	1.70	0.128	0.36	0.36	0.99	0.98	1.05	0.73
Q-Factor	2.03*	0.068	0.38	0.30	1.04	1.09	0.64	0.83
FF5M	1.76	0.113	0.40	0.29	1.10	1.21	0.54	0.82
M6,1 portfolios								
CAPM	0.75	0.610	0.30	0.41	1.12	1.25	1.88	0.70
FF3M	0.60	0.728	0.29	0.40	1.09	1.18	1.84	0.70
Q-Factor	0.71	0.643	0.27	0.42	1.01	1.01	2.33	0.71
FF5M	0.54	0.780	0.27	0.41	1.00	0.99	2.29	0.70

Note: The table reports the model performance statistics for CAPM, FF3M, the q-factor and FF5M against portfolios sorted by β, ME, B/M, D/E, CBOP, ARs, AG2 and M6,1. Performance of models on zero-cost hedge portfolios are also included but they are excluded for the GRS test. The calculation of variables and factors is detailed in Table 2 and Table 3, respectively. Statistics provided include the following: the GRS statistics, the absolute value of average intercepts ($A. \lvert\alpha_i\rvert$), the average standard errors of intercepts ($A. s(\alpha_i)$), the ratio of average absolute value of intercept to average absolute value of average excess portfolio returns minus average V-W market portfolio return ($A.\ |\alpha_i|\ /\ A.\ |\bar{r}_i|$), its squared version ($A.\ \alpha_i^2\ /\ A.\ \bar{r}_i^2$), the ratio of the squared average value of standard errors of intercepts to average value of squared alphas ($A.\ s^2\ (\alpha_i)\ /\ A.\ \alpha_i^2$), and the average adjusted coefficient of determination ($A.\ (R^2)$). The period is from July 2006 to December 2015. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

4.4. FACTOR SPANNING TESTS

We perform factor spanning tests to identify if there are any redundant factors. According to Huberman and Kandel (1987), a factor does not add anything to the mean-variance efficiency of a tangency portfolio if its variation is absorbed by the remaining factors.

Each time we represent LHS factor by one of the factors of the FF5M and right-hand side factors by the remaining four factors. Panel A of Table 16 presents spanning tests for the FF5M which uses factors that is constructed considering market and big stocks' breakpoints. According to the results, only HML extracts a significant intercept ($\alpha = 0.93$; $t = 1.70$; $p < 0.10$) when exposed to the remaining four factors. In contrast, the intercept from the exposure of market portfolio to the other factors is low and insignificant. However, it is 8 basis points larger than the average equity premium in Panel A of Table 6. This is largely due to the negative strong coefficient of RMW. The SMB regressions tell a similar story. The intercept from the exposure of SMB to the other four factors is insignificant, whereas it is 26 basis points larger than that of the SMB premium. This difference is large and due to the large HML exposure of the factor SMB. In the HML regression, the difference between the intercept and HML premium is 17 basis points. This difference is due to negative SMB exposure. Finally, consistent with the prior findings, the RMW intercept is very low and the CMA intercept is negative.

Panel B of the Table 16 replicates the factor spanning test for the FF5M which uses factors that is constructed considering the sample breakpoints. The findings are virtually the same, with some minor differences. For example, the intercept estimates are lower compared to the intercept estimates in Panel A of Table 16. The factor HML becomes insignificant and the remaining intercepts produces lower t-stat. Accordingly, Panel A factors which are constructed using market and big stocks' breakpoints are less redundant.

We replicate the spanning tests for the FF5M with E-W factors and present the results in Appendix 7. In addition, we perform similar spanning tests for the FF3M and q-factor model and present the results in Appendices 8 and 9, respectively. The conclusions are the same for all the cases.

Table 16: Spanning Tests on Five Factors

	V-W 2x3 factors of FF5M						
Panel A: Factors constructed based on market and big stocks' breakpoints							
	α	*$R_M - r_f$*	*SMB*	*HML*	*RMW*	*CMA*	*R^2*
$R_M - r_f$							
Coef.	0.21		-0.14	0.03	-0.92***	0.36	0.16
t-Stat.	0.32		-0.64	0.23	-4.76	1.46	
SMB							
Coef.	0.49	-0.04		-0.33***	-0.27*	-0.09	0.38
t-Stat.	1.21	-0.69		-5.20	-1.88	-1.00	
HML							
Coef.	0.93*	0.02	-0.69***		0.17	0.45	0.40
t-Stat.	1.70	0.22	-3.10		0.78	1.61	
RMW							
Coef.	0.08	-0.19***	-0.23*	0.07		0.16	0.31
t-Stat.	0.23	-5.17	-1.79	0.83		1.55	
CMA							
Coef.	-0.19	0.08*	-0.08	0.18*	0.16		0.20
t-Stat.	-0.49	1.82	-0.98	1.82	1.47		
Panel B: Factors constructed based on within portfolio breakpoints							
	V-W 2x3 factors of FF5M						
$R_M - r_f$							
Coef.	-0.02		-0.08	0.01	-0.63***	0.20	0.07
t-Stat.	-0.03		-0.47	0.06	-3.82	1.11	
SMB							
Coef.	0.41	-0.02		-0.40***	-0.24	-0.06	0.40
t-Stat.	0.98	-0.50		-5.80	-1.63	-0.70	
HML							
Coef.	0.68	0.00	-0.68***		0.02	0.38*	0.42
t-Stat.	1.55	0.06	-4.14		0.11	1.80	
RMW							
Coef.	-0.21	-0.15***	-0.25	0.01		0.24*	0.25
t-Stat.	-0.58	-3.89	-1.54	0.11		1.96	
CMA							
Coef.	0.06	0.05*	-0.06	0.23**	0.24*		0.24
t-Stat.	0.14	1.85	-0.73	2.16	1.85		

Note: Panel A reports the results from spanning regressions for the factors constructed using market and big stocks' breakpoints. Excess return on the market ($R_M - r_f$) portfolio represented by V-W returns on the sample stocks each year. The SMB, HML, RMW and CMA are size, value, profitability and investment mimicking portfolios constructed based on 2x3 sorts using market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. Detailed description of factor calculation provided in the Table 2 and the calculation of variables provided in Table 3. Panel B repeats the entire analysis with factors that uses sample stocks to calculate breakpoints. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

4.5. INVESTMENT OPTIMIZATION AND MAXIMUM SHARPE RATIO

To test the robustness of our findings and measure the economic significance of the models, we perform factor optimization. Table 17 provides the maximum ex-post Sharpe Ratios and optimal portion of investment to each of the factors according to the results of the optimization process.

Panel A of Table 17 provides details related with the optimized factors for the models which uses factors constructed considering the market and big stocks' breakpoints. CAPM produces a maximum ex-post reward-to-volatility ratio of 0.017, which is too low due to low premium and high SD of the market portfolio. FF3M produces a Sharpe ratio of 0.164, which is only 0.001 point lower than that of FF5M. Optimized weights favors factors SMB (53.2%) and HML (44.0%). In contrast, process suggest only 2.79% of investment to the market portfolio. This is due to its lower returns and higher variability. When the equations exclude HML, the ex-post Sharpe ratio drops dramatically to 0.061[90]. This finding demonstrates the economic importance of the HML factor since it effects return-to-volatility characteristics of candidate tangency portfolios. However, it is evident that the RMW and CMA factors does not improve the return-to-volatility characteristics of the tangency portfolio. Optimization process suggest only 5.71% of investment to the RMW. In contrast, due its negative returns, optimal investment to CMA is zero. These findings justify the irrelevancy of these factors.

We replicate the same optimization procedure for the factors that uses sample breakpoints to check the robustness of our factor construction methodology. According to the results, extracted reward-to-volatility ratios are lower than those of factors which uses market and big stocks' breakpoints[91]. Therefore, regardless of the methodology applied to construct the factors, RMW and CMA performs poor.

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[90] We replicate the same optimization procedure for E-W factors. Results are in Appendix 10.
[91] This is not true for the E-W factors.

Table 17: Optimized Portfolios and Maximum Ex-post Sharpe Ratios

	Optimized Weights for V-W Factors							
	$R_M - r_f$	*SMB*	*HML*	*RMW*	*CMA*	E(r)	SD	Sharpe Ratio
Panel A: Optimization for factors using market and big stock breakpoints								
CAPM	100%					0.258	9.16	0.017
FF3M	2.79%	53.2%	44.0%			0.461	2.80	0.164
Q-Factor	14.3%	46.3%		39.4%	0.00%	0.144	2.35	0.061
FF5M	3.68%	50.5%	40.1%	5.71%	0.00%	0.429	2.60	0.165
Panel B: Optimization for factors using within portfolio breakpoints								
CAPM	100%					0.258	9.16	0.017
FF3M	2.89%	52.1%	45.0%			0.381	2.62	0.145
Q-Factor	6.73%	50.8%		0.22%	42.5%	0.182	2.79	0.065
FF5M	2.86%	51.9%	44.6%	0.00%	0.01%	0.380	2.61	0.145

Note: Panel A reports the results for optimization on factors which uses market and big stocks breakpoints. We represent excess return on the market ($R_M - r_f$) portfolio by V-W returns on the sample stocks each year. The SMB, HML, RMW and CMA are size, value, profitability and investment portfolios that we construct based on 2x3 sorts using market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. We provide details for factor calculations in Table 2 and variables in Table 3. Panel B replicates entire analysis for the factors that uses sample breakpoints.

CHAPTER FIVE
DISCUSSION

Chapter five provides the discussions and the implications of our findings.

5.1. VARIABLE ATTRIBUTES

We investigate variable attributes and compare our results with those of the other studies. First, our results related with the average ROA of the firms listed in BIST is comparable with the results of Amman et al. (2012) related with ROA of firms from EU markets. In contrast, BIST firms are considerably less profitable, based on CBOP, with higher ARs compared to the results of Ball et al. (2016) related with the U.S. firms. Accordingly, consistent with Ball et al. (2016), firms that appear to be profitable according to earnings, are less profitable according to cash in BIST. The results from the correlation analysis support this finding (see Table 4). Consistent with Sloan (1996) we observe a negative correlation between ARs and ME and a positive correlation between profitability and ME. This finding demonstrates that the ARs effect returns negatively, whereas, profitability effect returns positively.

We then investigate the corporate investment attributes and compare our results with those of Ammann et al. (2012). According to our results, the average IG rate in BIST is considerably higher than the average IG rate of developed EU markets. This finding is not surprising since BIST is still developing. However, the relationship between corporate investment variables and valuation variables found as weak in contrast to the speculations of the equation 3 of FF (2006).

Results related with market capitalization of firms reveals tremendous devaluation of TL against U.S. Dollars in the past half-decade. Accordingly, average valuation ratio (B/M) of BIST is increasing. For example, Gönenç and Karan (2003) report a mean B/M of 0.61 from 1992 to 1996. According to our results, mean B/M ratio is at least 30 basis points higher during our sampling period. Additionally, mean B/M ratio of BIST is at least 15 to 20 basis points higher than the developed EU markets compared to the results of Amman et at. (2013) and other developing markets compared to the results of Çakici et al. (2013). This result indicates that BIST investors can buy more of a book asset for the given value of a Dollar compared to an equivalent investment to other markets. For this reason, we expect a strong value effect in BIST. Finally, consistent with the theory of CAPM, the mean and median β is almost 1. Therefore, there should be a strong β-return relationship in BIST.

5.2. FACTOR ATRIBUTES

We investigate factors that mimic market, small, value, robust profit and conservative investment strategies. Results indicate that, regardless the methodology we use to construct them, these factors have insignificant premiums in BIST.

From an economical point of view, compared to the results of Guo et al. (2017), FF (2016 and 2017) and Zaremba and Czapkiewicz (2017), the equity premium in BIST is at least 32 to 76 basis points lower than those of developed and other developing markets. However, compared to the results of FF (2017), it is 14 basis points higher than that of Japan. In contrast, the Sharpe Ratio of the market factor of BIST is comparable with that of Japan and considerably lower than the Sharpe Ratios of other markets, the differences are at least 7 to 13 basis points. Our SMB premium is comparable with the SMB premium of the U.S. market, documented by FF (2016), and it is at least 3 to 36 basis points higher than the SMB premiums of Asia Pacific, developed Europe, Japan, documented by FF (2017), and Australia, documented by Chiah et al. (2016), markets. Except for the U.S., SMB premiums of these markets are also insignificant. Additionally, our factor SMB provides a better Sharpe Ratio compared to those of developed Europe, Japan, Asia Pacific and Australia markets. In addition, our HML premium is economically high. For example, compared to the results from it is at least 17 to 44 basis points higher than those of Australia, documented by Chiah et al. (2016), Asia Pacific, developed Europe, Japan, documented by FF (2017), and the U.S., documented by FF (2016), markets. However, due to high SDs, it provides a better Sharpe Ratio than that of only North America. In contrast, our RMW premium is negligible like the RMW premium of the Japanese market, documented by FF (2017) and Kubota and Takehara (2017). And, the CMA premium is negative like the negative CMA premiums of the Japanese, Chinese and developing Eastern Europe, documented by Guo et al. (2017), Kubota and Takehara (2017) and Zaremba and Czapkiewicz, (2017), markets.

There can be a simple explanation underlying the large yet insignificant premiums on market, SMB and HML factors. The high variability of factor returns and short sampling period[92].

5.3. AVERAGE RETURN ON PORTFOLIOS

This section discusses the results of portfolio sorts and the performance of models.

5.3.1. Beta, Returns and Models

Empirical evidence from Black et al. (1972), FF (1992 and 2016), Friend and Blume (1970), Rainganum (1981a) and Rouwenhorst (1999) suggest a flat relationship between the β and average returns. Our results oppose to these findings such as average returns are systematically increase with β in BIST. We reveal a monthly β premium of 1.20 percent which is significant at 10 percent level. This premium stayed significant when evaluated against CAPM and q-factor models. Therefore, we cannot support *Hypothesis 1,* speculating that the return-β relationship is flat.

5.3.2. Market Capitalization, Returns and Models

We document a monthly size premium of 0.90%, which is economically large but not statistically significant. This finding is a norm for the developing markets due to

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[92] SD and number of observations (n) have important roles in the calculation of the t-stat. Higher the SD and lower the n results in a low t-stat. Formally; $t = \frac{\bar{x}-\mu}{SD/\sqrt{n}}$, where the numerator is the difference between sample mean and zero and the denominator is the ratio of SD to the square root of observations.

high SD of returns. Results from Çakici et al. (2013) and De Moore and Sercu, (2013) are two examples. On the other hand, our findings contradict with Ersalan (2012) and Gönenç and Karan (2003), they document a negative size premium for the BIST.

Consistent with Chan and Chen (1991), a portfolio consisting of the lowest ME stocks has higher D/E ratio and lower profit than a portfolio consisting of the highest ME stocks. In addition, zero-investment portfolio of small stocks is not exposed to β. Therefore, we can support *Hypotheses 2a* and *2b*, speculating that small stocks are riskier than big stocks and CAPM cannot explain their returns. Consequently, in the spirit of FF (1993)[93], the inclusion of SMB into the pricing equation is appropriate for the pricing of securities listed on BIST since CAPM is not a complete description for portfolios sorted by ME.

5.3.3. B/M Ratio, Returns and Models

Our monthly value premium is economically large and statistically significant (1.69; $p < 0.05$). This monthly premium is higher than those of developed markets, compared to the results of Ali et al. (2012), Ammann et al. (2012), Anderson and Brooks (2006), Capaul et al. (1993), Chen and Zhang (1998), FF (1992 and 1998) and Novy-Marx (2013), and comparable with those of other developing markets, compared to the results of FF (1998), Lischewski and Voronkova (2012) and Rouwenhorst (1999). However, our finding rejects Gönenç and Karan (2003), who document a negative value premium for BIST securities from 1992 to 1996.

Consistent with Chan and Chen (1991) and FF (1995), a portfolio consisting of value stocks has lower profit than a portfolio consisting of growth stocks. In addition, returns on zero-investment portfolio of value stocks cannot be explained by the CAPM. Therefore, we can support *Hypotheses 3a* and *3b*, speculating that value stocks are riskier than growth stocks and CAPM cannot explain their returns. Consequently, in the spirit of FF (1993)[94], the inclusion of HML into the pricing equation is appropriate for the pricing

[93] See also Merton (1973) and Ross (1976).
[94] See also Merton (1973) and Ross (1976).

of securities listed on BIST since CAPM is not a complete description for portfolios sorted by B/M. However, our results further indicate that the recent models of asset pricing cannot explain the returns on the zero-investment portfolio of value stocks. Therefore, we cannot conclude that these models provide complete description of average BIST returns.

5.3.4. D/E Ratio, Returns and Models

In contrast to Zaremba and Czapkiewicz (2017), who report a negative D/E premium for a portfolio consisting of five emerging markets, we document a positive yet insignificant D/E premium on a zero-investment portfolio of high D/E stocks. In addition, according to the results, a portfolio consisting of stocks with higher D/E ratio tend to be more sensitive to the movements in the market portfolio than that with lower D/E ratio. This finding confirms the prior findings such as highly leveraged stocks tend to be more sensitive to the movements in the systematic risk factor and underlying economic forces.

5.3.5. Profitability, Returns and Models

We observe a weak profitability effect in BIST. In contrast to the speculations of equation 3, the relationship between the profitability variables and E-Rs is not linear and insignificant, hence; our findings are inconsistent with the predictions of FF (2006) and the findings of Ball et al. (2015 and 2016) and Novy-Marx (2013). Therefore, we are not able to support *Hypothesis 5a*, speculating a positive linear relationship between firm profitability and average returns. From an economic point of view, consistent with Ball et al. (2016) premium on the zero-investment portfolio of profitable stocks is positive yet it is considerably lower than that of U.S. market. Consistent with equation 3, the portfolio consisting of profitable stocks has lower average B/M ratio than the portfolio consisting of unprofitable stocks. In addition, according to models, p5 has a positive exposure to factor HML. Therefore, we can support *Hypothesis 5b.* This finding contradicts Novy-Marx (2013) who document a growth tilt for profitable firms in the U.S. market.

Finally, consistent with Ball et al. (2016), we show that, a CBOP variable, which is completely free from ARs, produce at least 21 to 64 basis points larger premiums in the sorts than the earnings based profitability variables (i.e. ROA, ROE, GP and OP). This finding contradicts Novy-Marx (2013). In addition, considering this finding, we can support *Hypothesis 5d*, speculating that the CBOP is more informative related with E-Rs than the AR-based earnings. In contrast, we cannot support *Hypothesis 5c* due to insufficient profitability-return relationship.

4.3.6. Accruals, Returns and Models

The average monthly ARs premium is 0.27% in BIST, however, this premium is insignificant. Therefore, we cannot support *Hypothesis 5d* speculating that there is a negative relationship between ARs and returns. Models justify this insignificance. This finding is consistent with that of Zaremba and Czapkiewicz (2017) who document an insignificant AR premium for a portfolio consisting low AR stocks from five emerging markets. In contrast, the economic magnitude of our AR premium is almost equal to that of the U.S. market documented by Ball et al. (2016).

Finally, a portfolio consisting of low AR stocks loads positively on factor RMW, hence; its returns tilt toward profitable stocks. These results justify Ball et al. (2016) and prior findings on the current topic; for example, firms that appear profitable based on earning are less profitable based on cash.

5.3.7. Investment, Returns and Models

In contrast to the speculations of equation 3, our results indicate weak corporate investment effect in BIST. The relationship between E-Rs and corporate investment is non-linear and insignificant. Models justify this finding, hence; we cannot support *Hypothesis 6a* speculating a negative linear relationship between corporate investment and returns. This finding is consistent with that of Zaremba and Czapkiewicz (2017) who observe an insignificant corporate investment effect on a low corporate investment portfolio consisting of stocks from five emerging markets. In addition, due to this insignificant relationship we cannot support *Hypothesis 6b.*

Finally, among three different corporate investment proxies, AG2 variable produce at least 25 to 35 basis points larger variations in sorts. This finding is consistent with that of Cooper et al. (2008).

5.3.8. Momentum, Returns and Models

We analyze two different momentum strategies, trading based on past twelve-month returns twelve-month holding period and trading based on past six-month returns twelve-month holding period. Consistent with Bildik and Gülay (2007), our results indicate a negative return for the former strategy whereas, consistent with Ersoy and Ünlü (2013) premium for the latter strategy is positive, economically large (0.59 percent) but statistically insignificant. Models justify the insignificance of this momentum premium. Therefore, we cannot support *Hypothesis 4a* speculating that there is a momentum effect in historical stock returns. It can be concluded that BIST is weakly efficient.

In contrast, when we evaluate models against momentum returns, we cannot observe any factor exposure. Interestingly, the looser portfolio has higher exposure to β than the winner portfolio. These results partially support *Hypothesis 4b,* speculating that CAPM cannot explain the momentum effect. According to Conrad and Kaul (1998), the underlying reason behind the momentum effect is risk. In contrast, our results show that past winner stocks are bigger with lower D/E ratio and higher profits compared to those of past loser stocks.

5.4. MODEL PERFORMANCES, SPANNING TESTS AND OPTIMIZATION

Empirical evidence suggests that CAPM fails to explain average returns on portfolios constructed based on several firm specific characteristics. General tendency aims to resolve and explain these pricing inefficiencies manifest itself as the augmentation of CAPM with additional factors. In the current thesis, we examine the performances of such factor models in BIST.

First, we test the mean-variance efficiency of the factors. The findings are obvious, we cannot conclude that models can provide complete description of average returns in BIST since they are not able to explain returns on a portfolio consisting of value stocks. Therefore, they fail in the GRS test. Additionally, CAPM and q-factor model fail the GRS test since they cannot explain returns on a portfolio consisting of low AG2 stocks. For the rest, models pass the test since the variation in returns related to other variables is weakly/not significant.

We then focus our attention to economic significance of models. Consistent with our prior findings, models attribute entire variations in portfolios sorted by ME, CBOP, ARs and M6,1 to sampling errors. For the other cases, FF3M always outperforms CAPM and the q-factor model in explaining returns on portfolios sorted by B/M, β and AG2. The performances of FF3M and FF5M against these sorts are indistinguishably close. These findings contradict with those of FF (2015 and 2017).

We perform factor spanning regression test to see if there are any redundant factors. Our results reveal the importance of factor HML. Statistically speaking, HML extract significant intercept when exposed to the remaining factors. In contrast, the RMW intercept is found as very low and the CMA intercept is found as negative; hence, our results contradict with Hou et al. (2016) and FF (2015, 2016 and 2017) who document the redundancy of factor HML.

Finally, we supplement our findings with factor optimization. According to Guo et al. (2017), a combination of factors that produce the maximum ex-post Sharpe Ratio can price any asset since the combination represent the tangency portfolio in the spirit of Huberman and Kandel (1987). Consistent with our prior findings, Sharpe Ratios for the FF3M and FF5M are equal. In addition, their ex-post maximum Sharpe ratios are considerably higher than those of CAPM and the q-factor model. These findings justify the irrelevancy of RMW and CMA factors and contradict with FF (2015, 2016 and 2017).

Consequently, our findings show that recent factors of RMW and CMA do not improve the performance of FF3M, whereas the factors of SMB and HML improve the performance of CAPM. Indicating the failure of clean surplus relation and q-theory of investment in BIST.

CONCLUSION

This thesis is motivated by the guidance of CAPM, the valuation equation of FF (2006), q-theory of investment and prominent empirical evidence and tests the performances of CAPM, FF3M, the q-factor model and FF5M against related and unrelated pricing anomalies, such as β, ME, B/M, D/E, profitability, ARs, corporate investment and momentum for a developing market namely BIST from July 2006 to December 2015.

Initially, we perform univariate portfolio analysis to examine whether β, size, B/M, D/E, profitability, ARs, investment and momentum can significantly predict future returns. We then focus on the model performance statistics to test the economic significance of additional factors over the market factor of CAPM. Additionally, we test the mean-variance efficiency for these factors using the GRS and spanning regression tests and supplement our findings with portfolio optimization.

The existing asset pricing and anomalies literature concerning with the BIST stocks considers only the traditional models of asset pricing such as CAPM and FF3M. Additionally, existing studies overlook recent market anomalies such as the multi-identity profitability anomaly and corporate investment anomaly. According to our knowledge, these patterns have never been investigated for BIST stocks. Additionally, we are unaware of any empirical work that augment FF5M with a cash-based profitability factor. BIST provides a nice setting for this test since emerging markets such as BIST can give rise to aggressive use of ARs. CBOP is completely ARs free and rather reflect the impact of cash earnings that is relevant to dividends. According to equation 3, its use is appropriate in the FF5M tests. In addition, there is no study testing the performances of the FF5M and q-factor model on BIST stocks. These central issues of the modern portfolio and asset pricing theory must have significant economic implications and are important for the practitioners, academics and policy makers those who have interest for BIST stocks.

In this context, we can list our contributions and uses of our results as follows; first, this thesis is the first to augments a cash-based profitability factor with FF5M. In their study, FF (2015) use earnings before extraordinary items as a proxy for the expected profitability effect. However, earnings include ARs that are not relevant to dividends since they represent accounting numbers and not cash earnings. Theoretically speaking, we think that investors, portfolio managers and academics should augment FF5M with a cash-based profitability factor in its tests, as equation 3 speculates.

Second, to our knowledge, there is no study investigating the relationship between E-Rs and cash-based profitability and E-Rs and corporate investment for the stocks listed on BIST. This thesis is the first to test these relationships in BIST. Additionally, it is the first to test the performances of FF5M and q-factor model of Hou et al. (2016) for the BIST against related and unrelated market anomalies.

Third, we examine eight broad categories of market anomalies including fifteen different variables. We evaluate both the E-W and V-W investment strategies. Our findings reveal the superiority of V-W investment strategy for almost all the cases. Therefore, different from the studies that investigate anomalies in developing markets, like the study of Rouwenhorst (1999), results of this thesis are not limited to E-W portfolio investment strategy. Additionally, from an investor viewpoint, we document eight unique V-W investment strategies that yields positive premiums. The economic magnitude for these strategies are too big to be disregarded. To be more specific, BIST investors can be better off by including stocks with high β, low ME, high B/M, high D/E, high profits, low ARs, low AG and winning prior returns in their active portfolios.

Fourth, for the first time, we provide the content for the best combination of tangency portfolio, a portfolio that yields the highest possible reward-to-volatility ratio given our factors. According to Guo et al. (2017), a combination of factors which produce the highest Sharpe Ratio can price any asset. We evaluate different combinations for five different factors. Our results indicate the irrelevancy of recent factors RMW and CMA on the risk-return characteristics of the tangency portfolio. This means that, clean surplus relationship and q-theory of investment fails in the pricing of BIST common stocks. Academics should search for more appealing theories that can improve the pricing performance in emerging market settings. At this stage, it can be said that academics, portfolio managers, policy makers and investors should not bear the cost of constructing factors RMW and CMA when estimating the cost of equity, testing the robustness of their empirical findings or measuring the abnormal returns in event studies. FF3M can perform these tasks at least as well as FF5M and far better than CAPM and the q-model in BIST.

Fifth, policy makers can use our methodology to construct factors and estimate the cost of equity to use it in strategic governmental decision taking in Turkey. We provide evidence related with different factor construction methodologies. Our portfolio optimization results indicate that V-W factors that uses market and big stocks' breakpoints provides steeper reward-to-volatility line compared to factors that uses sample breakpoints. Additionally, investors can more efficiently evaluate the portfolio manager's performance using our factor construction methodology.

Sixth, we conduct different sorts to pick profitability, investment and momentum variables; hence, our variable choices are not arbitrary. We reveal that a cash-based profitability variable, growth rate in total book assets lagged by 2 years and trading based on prior six-month performances produce larger variations in E-Rs than the other proxies. Therefore, we advise investors, policy makers, portfolio managers and academics to consider these variables as a proxy for the profitability, investment and momentum effects when conducting fundamental analysis on BIST common stocks.

Finally, this thesis provides an out-of-sample evidence for an emerging market case related with the market anomalies and asset pricing literature other than the U.S. and other developed markets.

Our analysis is from July 2006 to December 2015. Univariate portfolio analysis reveals large positive monthly (risk adjusted) premiums ranging from 0.17% (0.06) to 1.69% (1.65) for zero-investment portfolio strategies. These premiums are economically larger (comparable) than those of developed (developing) markets that is documented by Ammann et al. (2012), Ball et al. (2016), FF (2015, 2016 and 2017), Zaremba and Czapkiewicz (2017) and others. However, only the B/M and β premiums are statistically significant. The models also justify the B/M effect. One of the main reasons behind the statistical insignificance of other strategies is their high return variability.

The findings related with the performance of the models are interesting. For example, all the models fail to explain returns on portfolio composed of high B/M stocks. According to the asset pricing tests, the main problem for these models is their failure to capture the high average returns on the portfolio of value stocks whose returns behave like those of small and unprofitable firms with aggressive investment. Accordingly, the models fail in the GRS test against the B/M effect. This finding demonstrates that the factors of these models are not mean-variance efficient; hence, it cannot be concluded that they provide a complete description for average BIST returns. For the rest of the sorts, the models point out two possibilities: (i) they either attribute most (all) of the variation to the sampling errors and/or (ii) the SD of returns on these portfolios are too high; therefore, they lack statistical significance and cannot extract significant t-stat. values. Accordingly, the models can easily pass the GRS test against these portfolios. However, this result is not due to the mean variance-efficiency of the factors; instead the excess returns resulting from the investigation variables are not high enough to cause any problem for the models.

In addition, the results related with the model test statistics and fundamental portfolio characteristics suggest that augmenting CAPM with size (SMB) and value (HML) factors is appropriate insomuch that these factors considerably improve the pricing performance. Consistent with Chan and Chen (1991), small stocks have a higher average debt ratio compared to big stocks. In addition, consistent with FF (1995), value stocks have lower average profitability compared to growth stocks. Further, zero-investment portfolios of small and value stocks are not exposed to β. Therefore, in the spirit of FF (1993), CAPM should be augmented with the factors of SMB and HML for the pricing of BIST securities. However, the findings also suggest that the relationship between the parameters of equation 3 (i.e. profitability and investment) and E-Rs is too weak and insignificant. Therefore, inconsistent with FF (2006, 2015 and 2016) and Hou et al. (2016), the factors of profitability (RMW) and investment (CMA) are unnecessary. Analogously, the test performance statistics, spanning regressions and portfolio optimization justify this conclusion. The RMW and CMA never improve the pricing or economic performances of FF3M, whereas SMB and HML improve both the pricing and economic performances of the CAPM. Finally, the q-factor model, which drops HML, always underperforms FF3M and FF5M based on alpha dispersion and the Sharpe Ratio. The spanning tests results, factor coefficients, alpha estimates and portfolio optimization support the importance of the HML factor for the pricing of BIST securities.

Consequently, the findings of this thesis are inconsistent with those of FF (2006, 2015, 2016 and 2017) and Hou et al. (2016) and indicate that the clean surplus relationship fails to represent dividends and cannot account for the pricing behavior in an emerging market. The same is true for the q-theory of investment.

Our aim was not to reveal an equation that provide a perfect description of average returns on BIST securities, besides according to empirical evidence this aim is far too optimistic. Rather, our aim is in line with that of FF (2017). According to them "… there is value in searching for a small set of LHS portfolios that span the Markowitz (1952) mean variance efficient set and so capture E-Rs on all assets" (FF, 2017: 18). We believe that future asset pricing tests can be extended to models which augments momentum and liquidity factors.

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APPENDICES

APPENDIX 1: Excess Returns on Portfolios Sorted by Profitability Variables

	2006 to 2015				*2006 to 2009*				*2010 to 2015*			
					Panel A: GP							
Portfolio	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n
p1	0.23	0.52	13.1	47	1.68	1.06	17.2	40	-0.83	0.14	10.2	51
	(0.20)	(0.47)			(0.70)	(0.45)			(-0.97)	(0.17)		
p5	0.54	0.16	10.5	26	1.02	0.82	11.9	24	0.19	-0.32	9.53	30
	(0.59)	(0.22)			(0.56)	(0.59)			(0.22)	(-0.42)		
Hedge	0.31	-0.36			-0.65	-0.24			1.01***	-0.45		
p5-p1	(0.70)	(-0.58)			(-0.76)	(0.18)			(3.14)	(-0.92)		
					Panel B: OP							
p1	0.26	-0.02	13.8	54	1.39	0.31	17.4	55	-0.57	-0.26	11.2	53
	(0.23)	(-0.02)			(0.64)	(0.13)			(-0.64)	(-0.27)		
p5	0.57	0.05	9.27	21	0.77	0.16	9.5	19	0.42	-0.03	9.10	26
	(0.60)	(0.07)			(0.40)	(0.11)			(0.47)	(-0.04)		
Hedge	0.31	0.07			-0.62	-0.14			0.99**	0.23		
p5-p1	(0.75)	(0.10)			(-0.88)	(-0.10)			(2.17)	(0.36)		
					Panel C: CBOP							
p1	0.36	0.02	13.0	52	1.52	0.68	16.3	51	-0.48	-0.47	10.6	53
	(0.37)	(0.01)			(0.82)	(0.28)			(-0.49)	(-0.52)		
p5	0.58	0.29	10.3	25	0.84	0.53	10.3	22	0.39	0.12	10.3	26
	(0.34)	(0.37)			(0.53)	(0.34)			(0.40)	(0.15)		
Hedge	0.21	0.28			-0.69	-0.15			0.87**	0.58		
p5-p1	(0.59)	(0.46)			(-1.08)	(-0.12)			(2.09)	(1.33)		
					Panel D: ARs							
p1	0.32	0.21	11.5	34	0.56	0.20	12.9	30	0.14	0.22	10.5	38
	(0.35)	(0.21)			(0.33)	(0.10)			(0.25)	(0.27)		
p5	0.27	-0.06	10.7	38	0.77	-0.10	11.7	32	-0.11	-0.03	10.0	41
	(0.26)	(-0.06)			(0.36)	-(0.05)			(-0.13)	(-0.03)		
Hedge	0.05	0.27			-0.22	0.30			0.25	0.24		
p1-p5	(0.14)	(0.55)			(-0.41)	(0.36)			(0.66)	(0.40)		
					Panel E: ROA							
p1	0.17	0.13	10.4	60	1.15	0.86	15.1	56	-0.54	-0.39	11.4	62
	(0.16)	(0.12)			(0.53)	(0.38)			(-0.59)	(-0.39)		
p5	0.36	0.02	9.2	22	0.70	0.14	9.23	17	0.11	-0.07	8.39	25
	(0.40)	(0.03)			(0.38)	(0.12)			(0.13)	(-0.09)		
Hedge	0.19	-0.12			-0.45	-0.72			0.65	0.32		
p5-p1	(0.47)	(-0.17)			(-0.63)	(-0.55)			(1.50)	(0.46)		
					Panel F: ROE							
p1	0.28	0.12	13.1	58	1.43	0.88	15.4	55	-0.56	-0.44	11.5	61
	(0.26)	(0.11)			(0.68)	(0.40)			(-0.63)	(-0.43)		
p5	0.31	0.13	9.2	22	0.50	0.28	9.48	18	0.17	0.02	7.69	24
	(0.32)	(0.18)			(0.26)	(0.20)			(0.19)	(0.03)		
Hedge	0.03	0.01			-0.94	-0.60			0.73	0.46		
p5-p1	(0.03)	(0.02)			(-1.31)	(-0.55)			(1.55)	(0.89)		

Note: Table shows monthly V-W and E-W excess returns on extreme deciles and hedge portfolios from July 2006 to December 2015. At the end of each June we allocate all the stocks into investment portfolios employing the 20^{th}, 40^{th}, 60^{th} and 80^{th} percentiles of profitability variables among the stocks. We rebalance portfolios annually. We provide the details for the calculation of the profitability variables in Table 2. We obtain SD and average number of firms (n) from the time series averages of cross-sectional SD and *n*. *** indicates statistical significance at the 1% level.

APPENDIX 2: Excess Returns on Portfolios Sorted by Investment Variables

	2006 to 2015				*2006 to 2009*				*2010 to 2015*			
					Panel A: AG1							
Portfolio	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n
p1	0.56	0.39	11.6	43	1.24	0.76	13.7	44	0.07	0.12	10.1	42
	(0.56)	(0.39)			(0.62)	(0.38)			(0.08)	(0.13)		
p5	0.36	0.56	12.1	31	1.13	1.26	15.0	23	-0.20	0.05	10.0	39
	(0.32)	(0.52)			(0.49)	(0.58)			(-0.22)	(0.06)		
Hedge	0.20	-0.17			0.11	-0.50			0.27	0.07		
p1-p5	(0.65)	(-0.34)			(0.18)	(-0.48)			(0.81)	(0.16)		
					Panel B: AG2							
p1	0.72	0.87	12.8	41	1.83	1.10	15.6	40	-0.10	0.70	10.7	42
	(0.66)	(0.77)			(0.82)	(0.47)			(-0.12)	(0.78)		
p5	0.34	0.69	11.2	32	0.58	1.82	11.2	28	0.17	-0.12	11.1	35
	(0.33)	(0.72)			(0.28)	(0.97)			(0.18)	(-0.13)		
Hedge	0.37	0.17			1.25**	-0.72			-0.26	0.82		
p1-p5	(0.99)	(0.28)			(2.10)	(-0.70)			(-0.63)	(1.28)		
					Panel C: IG							
p1	0.21	0.04	11.4	42	1.25	1.17	12.9	40	-0.54	-0.79	10.4	43
	(0.21)	(0.03)			(0.61)	(0.53)			(-0.61)	(-0.94)		
p5	0.08	0.12	10.9	30	0.66	0.56	13.0	27	-0.35	-0.20	9.41	32
	(0.08)	(0.12)			(0.32)	(0.27)			(-0.41)	(-0.24)		
Hedge	0.14	-0.08			0.59	0.61			-0.20	-0.59		
p1-p5	(0.58)	(-0.16)			(1.99)	(0.81)			(-0.62)	(-0.87)		

Note: Table shows monthly V-W and E-W excess returns on extreme deciles and hedge portfolios from July 2006 to December 2015. At the end of each June we allocate all the stocks into investment portfolios employing the 20th, 40th, 60th and 80th percentiles of corporate investment variables among big stocks. We rebalance portfolios annually. We provide the details for the calculation of the corporate investment variables in Table 2. We obtain SD and average number of firms (n) from the time series averages of cross-sectional SD and *n*. ** indicates statistical significance at the 5% level.

APPENDIX 3: Excess Returns on Portfolios Sorted by Momentum Variables

	2006 to 2015				*2006 to 2009*				*2010 to 2015*			
					Panel A: M6,1							
Portfolio	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n
p1	0.16	-0.17	12.0	42	1.47	0.25	14.2	37	-0.80	-0.48	10.4	45
	(0.15)	(-0.15)			(0.67)	(0.10)			(-0.95)	(-0.52)		
p5	0.06	0.42	12.2	29	0.07	1.05	12.4	24	0.06	-0.05	12.0	33
	(0.06)	(0.38)			(0.03)	(0.46)			(0.06)	(-0.05)		
Hedge	-0.09	0.59			-1.40*	0.81			0.85**	0.44		
p5-p1	(-0.22)	(0.91)			(-1.81)	(0.67)			(2.24)	(0.62)		
					Panel B: M12,1							
p1	0.53	0.62	12.7	45	1.98	1.57	16.6	34	-0.53	-0.07	9.88	53
	(0.47)	(0.60)			(0.85)	(0.74)			(-0.62)	(-0.08)		
p5	-0.07	0.01	12.0	29	0.16	0.51	12.8	26	-0.23	-0.34	11.5	31
	(-0.06)	(0.01)			(0.07)	(0.23)			(-0.24)	(-0.39)		
Hedge	-0.60	-0.61			-1.83*	-1.06			0.30	-0.27		
p5-p1	(-1.23)	(-0.92)			(-1.93)	(-0.80)			(0.89)	(-0.53)		

Note: Table shows monthly V-W and E-W excess returns on extreme deciles and hedge portfolios from July 2006 to December 2015. At the end of each June we allocate all the stocks into investment portfolios employing the 20th, 40th, 60th and 80th percentiles of momentum variables among big stocks. We rebalance portfolios annually. We provide the details for the calculation of the momentum variables in Table 2. We obtain SD and average number of firms (n) from the time series averages of cross-sectional SD and *n*. ** indicates statistical significance at the 5% level.

APPENDIX 4: Excess Returns on Portfolios Sorted by Other Variables

	2006 to 2015				2006 to 2009				2010 to 2015			
					Panel A: ME							
Portfolio	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n	$r^{E\text{-}W}$	$r^{V\text{-}W}$	SD	n
p1	0.99	0.98	14.3	21	2.49	2.45	16.5	19	-0.10	-0.10	12.7	22
	(0.84)	(0.83)			(1.11)	(1.10)			(-0.09)	(-0.09)		
p5	0.28	0.08	8.95	31	0.74	0.61	10.1	26	-0.05	-0.31	8.08	36
	(0.28)	(0.09)			(0.36)	(0.32)			(-0.06)	(-0.36)		
Hedge	0.71	0.90			1.75	1.84			-0.05	0.21		
p1-p5	(0.93)	(1.18)			(1.26)	(1.30)			(-0.07)	(0.27)		
					Panel B: B/M							
p1	-0.26	-0.07	11.0	23	0.42	0.25	12.8	22	-0.76	-0.30	9.54	25
	(-0.29)	(-0.09)			(0.22)	(0.16)			(-0.91)	(-0.40)		
p5	0.67	1.62	11.7	51	1.45	2.89	13.7	40	0.10	0.69	7.94	58
	(0.63)	(1.47)			(0.68)	(1.37)			(0.11)	(0.69)		
Hedge	0.94**	1.69**			1.04	2.65*			0.86	0.99		
p5-p1	(2.07)	(2.40)			(1.25)	(1.99)			(1.76)	(1.67)		
					Panel C: β							
p1	0.06	-0.38	12.4	32	0.87	0.03	16.3	30	-0.53	-0.68	9.63	34
	(0.06)	(-0.40)			(0.46)	(0.01)			(-0.56)	(-0.88)		
p5	0.18	0.81	11.1	32	0.75	1.68	11.7	25	-0.23	0.18	10.6	37
	(0.19)	(0.68)			(0.40)	(0.68)			(-0.23)	(0.19)		
Hedge	0.13	1.20*			-0.12	1.65			0.30	0.86		
p5-p1	(0.24)	(1.91)			(-0.09)	(1.33)			(0.98)	(1.63)		
					Panel C: D/E							
p1	0.71	0.22	13.0	32	2.23	0.91	17.4	26	-0.40	-0.28	9.85	36
	(0.72)	(0.22)			(1.17)	(0.47)			(-0.42)	(-0.27)		
p5	0.26	0.59	12.0	38	1.18	1.47	13.8	34	-0.41	-0.05	10.6	41
	(0.27)	(0.56)			(0.64)	(0.68)			(-0.42)	(-0.06)		
Hedge	-0.45	0.37			-1.05	0.56			-0.01	0.23		
p5-p1	(-0.96)	(0.75)			(-1.07)	(0.89)			(-0.03)	(0.31)		

Note: Table shows monthly V-W and E-W excess returns on extreme deciles and hedge portfolios from July 2006 to December 2015. At the end of each June we allocate all the stocks into investment portfolios employing the 20th, 40th, 60th and 80th percentiles of market capitalization (ME) that employs the 20th, 40th, 60th and 80th percentiles of BIST national market (following 2012 second national market also included into size breakpoint calculations due to its increased market share). To construct portfolio sorted by B/M, β and D/E, we use the 20th, 40th, 60th and 80th percentiles among big stocks. We rebalance portfolios annually. We provide the calculation of the variables in Table 2. We obtain SD and average number of firms (n) from the time series averages of cross-sectional SD and *n*. ** and * indicates statistical significance at the 5% and 10% levels.

APPENDIX 5: Factor Descriptive Statistics

	2006 to 2015					2006 to 2009					2010 to 2015				
	$R_M - R_f$	*SMB*	*HML*	*RMW*	*CMA*	$R_M - R_f$	*SMB*	*HML*	*RMW*	*CMA*	$R_M - R_f$	*SMB*	*HML*	*RMW*	*CMA*
Panel A: Mean returns, t-stat. and SDs of factors using market and big stock breakpoints															
	E-W 2x3 factors					*E-W 2x3 factors*					*E-W 2x3 factors*				
Mean	0.38	0.25	0.66	0.06	-0.10	1.16	0.75	0.50	-0.72	0.27	-0.18	-0.11	0.78	0.63**	-0.38
t-stat.	0.16	0.71	1.28	0.23	-0.31	0.56	1.07	0.46	-1.52	0.45	-0.22	-0.37	1.64	2.15	-1.14
SD	9.48	3.76	5.56	3.12	3.35	11.6	4.72	7.45	3.55	4.32	7.66	2.85	3.67	2.66	2.41
	V-W 2x3 factors					*V-W 2x3 factors*					*V-W 2x3 factors*				
Mean	0.15	0.23	0.76	0.04	-0.06	0.64	0.58	0.80	-0.80	-0.16	-0.21	-0.02	0.73	0.65**	0.02
t-stat.	0.16	0.47	1.12	0.09	-0.14	0.34	0.60	0.58	-0.86	-0.21	-0.28	-0.05	1.11	2.03	0.06
SD	8.74	5.15	7.58	4.48	4.18	10.6	6.51	10.2	5.62	5.40	7.14	3.92	5.03	3.34	3.06
Panel B: Mean returns, t-stat. and SDs of factors using within portfolio breakpoints															
	E-W 2x3 factors					*E-W 2x3 factors*					*E-W 2x3 factors*				
Mean	0.38	0.25	0.74	0.10	-0.08	1.16	0.88	0.45	-0.70	0.24	-0.18	-0.20	0.95**	0.68**	-0.32
t-stat.	0.16	0.70	1.69*	0.34	-0.23	0.56	1.28	0.48	-1.37	0.35	-0.22	-0.66	2.52	2.57	-0.97
SD	9.48	3.68	4.73	3.20	3.70	11.6	4.59	6.24	3.40	4.96	7.66	2.80	3.25	2.45	2.42
	V-W 2x3 factors					*V-W 2x3 factors*					*V-W 2x3 factors*				
Mean	0.15	0.24	0.56	-0.26	0.12	0.64	0.75	0.63	-1.17	0.05	-0.21	-0.13	0.51	0.41	0.17
t-stat.	0.16	0.46	0.96	-0.58	0.27	0.34	0.73	0.48	-1.34	0.05	-0.28	-0.27	1.22	1.19	0.51
SD	8.74	5.26	6.98	4.82	4.80	10.6	6.83	9.72	6.22	6.67	7.14	3.76	4.04	3.37	2.80

Note: From July 2006 till 2015 we construct V-W factors that mimic market, size, value, profitability and investment effects. The market portfolio represents average monthly returns on sample stocks each year. We provide the variable descriptions in Table 3. Panel A reports the average returns (mean), t-stat. and SD on returns of factors which uses market breakpoints. The calculation of market median ME considers all the stocks listed in BIST national market (following 2012 second national market also included due to its increased market share) at the end of each June. We also consider negative equity stocks and financials for the ME breakpoint calculation. Factors of HML, RMW and CMA uses December t-1 B/M, CBOP, and AG2 and splits stocks at 30^{th} and 70^{th} percentiles using only the big (B) stocks. Factors compose of the intersection of two size groups and three B/M or CBOP or AG2 groups. Panel B replicates the same analysis for the factors that uses sample breakpoints. We detail the factor calculations in Table 2. ** indicates statistical significance at the 5% level.

APPENDIX 6: Factor Correlations

Panel A: Correlations between factors constructed based on market and big stocks' breakpoints

	E-W 2x3 factors				
	$R_M - r_f$	*SMB*	*HML*	*RMW*	*CMA*
$R_M - r_f$	1.00	0.27***	-0.07	-0.30***	-0.00
SMB	0.27***	1.00	-0.28***	-0.20**	-0.03
HML	-0.07	-0.28***	1.00	0.27***	0.32***
RMW	-0.30***	-0.20**	0.27***	1.00	0.12
CMA	-0.00	-0.03	0.32***	0.12	1.00

Panel B: Correlations between factors constructed based on within portfolio breakpoints

	E-W 2x3 factors				
$R_M - r_f$	1.00	0.27***	-0.05	-0.29***	-0.03
SMB	0.27***	1.00	-0.30***	"-0.23***	-0.06
HML	-0.05	-0.30**	1.00	0.26***	0.34***
RMW	-0.29***	-0.23***	0.26***	1.00	0.24***
CMA	-0.03	-0.06	0.34***	0.24***	1.00

Note: Panel A reports the correlations between V-W factors that we construct using market breakpoints. Panel B reports the correlations between factors that we construct using sample breakpoints. We provide details for the factor construction in Table 2. *** indicates statistical significance at the 1% level.

APPENDIX 7: Spanning Tests on Alternative Five Factors

Panel A: Factors constructed based on market and big stocks' breakpoints

	E-W 2x3 factors of FF5M						
	α	$R_M - r_f$	SMB	HML	RMW	CMA	R^2
$R_M - r_f$							
Coef.	0.22		0.58***	0.10	-0.83***	0.07	0.11
t-Stat.	0.26		2.67	0.66	-2.95	0.27	
SMB							
Coef.	0.35	0.09*		-0.18	-0.09	0.07	0.12
t-Stat.	0.99	1.79		-1.68	-0.68	0.41	
HML							
Coef.	0.77*	0.03	-0.34		0.36	0.48	0.18
t-Stat.	1.69	0.62	-1.40		1.39	1.46	
RMW							
Coef.	0.04	-0.09**	-0.06	0.12		0.05	0.13
t-Stat.	0.14	-2.84	-0.70	1.54		0.58	
CMA							
Coef.	-0.26	0.01	0.06	0.20	0.06		0.08
t-Stat.	-0.86	0.27	0.40	1.45	0.58		

Panel B: Factors constructed based on within portfolio breakpoints

	E-W 2x3 factors of FF5M						
$R_M - r_f$							
Coef.	0.19		0.60***	0.16	-0.77***	0.07	0.10
t-Stat.	0.22		2.71	0.96	-3.15	0.30	
SMB							
Coef.	0.40	0.09*		-0.22**	-0.13	0.07	0.14
t-Stat.	1.12	1.76		-2.17	-1.30	0.47	
HML							
Coef.	0.82**	0.04	-0.35*		0.22	0.37	0.19
t-Stat.	2.08	0.87	-1.87		1.00	1.52	
RMW							
Coef.	0.09	-0.08**	-0.10	0.10		0.15	0.15
t-Stat.	0.33	-2.45	-1.30	1.00		1.46	
CMA							
Coef.	-0.31	0.01	0.07	0.25	0.21		0.12
t-Stat.	-0.91	0.31	0.46	1.54	1.51		

Note: Panel A reports the results from the spanning regressions for factors constructed using market and big stocks' breakpoints. Excess return on market ($R_M - r_f$) represented by E-W returns on a portfolio of sample stocks each year. The SMB, HML, RMW and CMA constructed based on 2x3 sorts using the market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. We provide details for the factor calculation in Table 2 and details for the variables in Table 3. Panel B repeats the entire analysis with factors which uses sample stocks to calculate breakpoints. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

APPENDIX 8: Spanning Tests on Q-Factors

	E-W 2x3 factors						V-W 2x3 factors					
	α	*$R_M - r_f$*	*SMB*	*RMW*	*CMA*	*R^2*	*α*	*$R_M - r_f$*	*SMB*	*RMW*	*CMA*	*R^2*
Panel A: Factors constructed based on market and big stocks' breakpoints												
$R_M - r_f$												
Coef.	0.30		0.55**	-0.79***	0.11	0.11	0.24		-0.16	-0.91***	0.37*	0.17
t-Stat.	0.33		2.60	-3.02	0.56		0.34		-0.93	-4.62	1.69	
SMB												
Coef.	0.23	0.09*		-0.16	-0.01	0.07	0.24	-0.05		-0.42**	-0.31	0.21
t-Stat.	0.65	1.79		-1.25	-0.07		0.51	-1.00		-2.20	-1.64	
RMW												
Coef.	0.14	-0.09***	-0.11		0.11	0.10	0.14	-0.20***	-0.28**		0.19	0.30
t-Stat.	0.59	-3.04	-1.36		1.13		0.45	-5.59	-2.37		1.52	
CMA												
Coef.	-0.12	0.02	-0.01	0.14		-0.01	-0.03	0.09**	-0.22	0.20		0.14
t-Stat.	-0.40	0.57	-0.07	1.09			-0.07	2.10	-1.69	1.44		
Panel B: Factors constructed based on within portfolio breakpoints												
	E-W 2x3 factors						*V-W 2x3 factors*					
$R_M - r_f$												
Coef.	0.32		0.54**	-0.74***	0.13	0.10	-0.02		-0.09	-0.63***	0.22	0.07
t-Stat.	0.35		2.38	-3.28	0.66		-0.02		-0.57	-3.86	1.24	
SMB												
Coef.	0.24	0.08*		-0.19	-0.02	0.07	0.19	-0.03		-0.34	-0.29	0.19
t-Stat.	0.65	1.71		-1.35	-0.10		0.40	-0.60		-1.73	-1.65	
RMW												
Coef.	0.18	-0.08**	-0.14		0.20	0.14	-0.20	-0.15***	-0.26*		0.25	0.25
t-Stat.	0.74	-2.60	-1.32		1.47		-0.59	-3.43	-1.68		1.63	
CMA												
Coef.	-0.11	0.02	-0.02	0.30		0.04	0.24	0.05	-0.24*	0.27		0.17
t-Stat.	-0.34	0.67	-0.10	1.37			0.59	1.41	-1.78	1.54		

Note: Panel A reports the results from the spanning regressions for factors constructed using market and big stocks' breakpoints. Excess return on market ($R_M - r_f$) represented by E-W (LHS of Panel A) and V-W (right-hand side of Panel B) returns on the sample stocks each year. by E-W returns on a portfolio of sample stocks each year. The SMB, RMW and CMA constructed based on 2x3 sorts using the market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. We provide details for the factor calculation in Table 2 and details for the variables in Table 3. Panel B repeats the entire analysis with factors which uses sample stocks to calculate breakpoints. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

APPENDIX 9: Spanning Tests on Three Factors

	E-W 2x3 factors					V-W 2x3 factors				
	α	$R_M - r_f$	*SMB*	*HML*	R^2	α	$R_M - r_f$	*SMB*	*HML*	R^2
Panel A: Factors constructed based on market and big stocks' breakpoints										
$R_M - r_f$										
Coef.	0.20		0.68***	0.00	0.06	0.13		0.06	0.01	-0.02
t-Stat.	0.21		3.35	0.03		0.14		0.30	0.08	
SMB										
Coef.	0.33	0.10**		-0.17	0.14	0.54	0.01		-0.40***	0.34
t-Stat.	0.99	2.03		1.50		1.24	0.29		-4.71	
HML										
Coef.	0.76*	0.00	-0.41		0.08	0.96*	0.01	-0.87**		0.34
t-Stat.	1.69	0.03	-1.11			1.79	0.08	-2.21		
Panel B: Factors constructed based on within portfolio breakpoints										
	E-W 2x3 factors					V-W 2x3 factors				
$R_M - r_f$										
Coef.	0.14		0.71***	0.07	0.06	0.12		0.07	0.01	-0.02
t-Stat.	0.14		3.37	0.53		0.13		0.40	0.09	
SMB										
Coef.	0.38	0.10**		-0.23	0.14	0.50	0.02		-0.46***	0.37
t-Stat.	1.13	2.00		-1.70		1.10	0.40		-4.81	
HML										
Coef.	0.83**	0.02	-0.40		0.08	0.76	0.00	-0.81**		0.37
t-Stat.	2.14	0.54	-1.35			1.60	0.08	-2.46		

Note: Panel A reports the results from the spanning regressions for factors constructed using market and big stocks' breakpoints. Excess return on market ($R_M - r_f$) represented by E-W (LHS side of Panel A) and V-W (right-hand side of Panel B) returns on the sample stocks each year. by E-W returns on a portfolio of sample stocks each year. The SMB and HML constructed based on 2x3 sorts using the market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. We provide details for the factor calculation in Table 2 and details for the variables in Table 3. Panel B repeats the entire analysis with factors which uses sample stocks to calculate breakpoints. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

APPENDIX 10: Portfolio Optimization for Alternative Factors

	Optimized Weights for E-W Factors							
	$R_M - r_f$	*SMB*	*HML*	*RMW*	*CMA*	E(r)	SD	Sharpe Ratio
Panel A: Optimization for factors using market and big stock breakpoints								
CAPM	100%					0.489	9.91	0.040
FF3M	4.32%	48.2%	47.4%			0.451	2.83	0.159
Q-Factor	10.3%	49.8%		40.0%	0.00%	0.190	2.31	0.082
FF5M	4.53%	46.1%	44.5%	4.86%	0.00%	0.430	2.70	0.160
Panel B: Optimization for factors using within portfolio breakpoints								
CAPM	100%					0.489	9.91	0.040
FF3M	2.23%	43.9%	53.8%			0.516	2.60	0.198
Q-Factor	9.44%	47.3%		43.3%	0.00%	0.196	2.18	0.090
FF5M	2.59%	41.8%	49.8%	5.82%	0.00%	0.488	2.45	0.199

Note: Panel A reports the results of optimization on factors which uses market and big stocks breakpoints. We represent the excess return on market ($R_M - r_f$) by E-W returns on the sample stocks each year. The SMB, HML, RMW and CMA constructed based on 2x3 sorts using the market breakpoints for two size groups and breakpoints among sample big stocks for three B/M, three CBOP and three AG2 groups. We provide details for the factor calculations in Table 2 and variables in Table 3. Panel B replicates entire analysis for the factors that uses sample breakpoints.

APPENDIX 11: Factor Loadings on Portfolio Returns Sorted by β

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p5 – p1)*
			Panel A: CAPM			
B_{CAPM}	0.96***	0.85***	1.07***	2.13***	1.17***	0.21***
	(20.4)	(17.3)	(22.7)	(26.3)	(31.9)	(3.18)
			Panel B: FF3M			
B_{FF3M}	0.96***	0.85***	1.06***	1.13***	1.17***	0.21***
	(21.0)	(17.3)	(23.3)	(27.5)	(37.7)	(3.58)
SMB_{FF3M}	-0.09	-0.07	0.22**	0.18	0.13	0.22
	(-1.29)	(-0.92)	(2.22)	(1.34)	(1.42)	(1.54)
HML_{FF3M}	-0.09*	-0.03	0.04	0.10	0.17**	0.25**
	(-1.85)	(-0.74)	(0.83)	(1.24)	(2.57)	(2.59)
			Panel C: Q-factors			
B_Q	0.97***	0.91***	1.09***	1.08***	1.13***	0.15**
	(21.3)	(20.2)	(23.0)	(25.5)	(27.4)	(2.21)
SMB_Q	-0.04	-0.03	0.28***	-0.00	-0.01	0.02
	(-0.58)	(-0.41)	(3.18)	(-0.03)	(-0.18)	(0.19)
RMW_Q	0.02	0.22**	0.19**	-0.29**	-0.20**	-0.22
	(0.28)	(2.04)	(2.37)	(-2.57)	(-2.00)	(-1.51)
CMA_Q	-0.11	-0.20**	0.12	-0.12	0.23*	0.34**
	(-1.47)	(-2.25)	(1.24)	(-1.24)	(1.95)	(2.27)
			Panel D: FF5M			
B_{FF5M}	0.97***	0.91***	1.09***	1.07***	1.12***	0.15**
	(22.2)	(20.1)	(22.9)	(25.7)	(30.8)	(2.41)
SMB_{FF5M}	-0.08	-0.04	0.28***	0.09	0.09	0.18
	(-1.19)	(-0.46)	(2.84)	(0.82)	(1.14)	(1.34)
HML_{FF5M}	-0.07	-0.01	0.00	0.14**	0.16***	0.23**
	(-1.43)	(-0.32)	(0.00)	(2.14)	(2.78)	(2.51)
RMW_{FF5M}	0.03	0.23**	0.19**	-0.32***	-0.23**	-0.26*
	(0.43)	(2.07)	(2.34)	(-2.79)	(-2.54)	(-1.92)
CMA_{FF5M}	-0.08	-0.20**	0.12	-0.07	0.16	0.23
	(-0.90)	(-2.14)	(1.16)	(-0.88)	(1.24)	(1.42)

Note: Appendix 11 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by β from July 2006 to December 2015. Numbers in parentheses represents *t-stat.* adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 12: Factor Loadings on Portfolio Returns Sorted by ME

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p1 - p5)*
			Panel A: CAPM			
B_{CAPM}	1.01***	1.04***	1.00***	1.01***	1.04***	-0.05
	(14.8)	(26.1)	(20.4)	(28.2)	(31.4)	(-0.30)
			Panel B: FF3M			
B_{FF3M}	0.99***	1.02***	0.99***	1.01***	1.04***	-0.05
	(21.3)	(41.2)	(39.2)	(29.1)	(31.1)	(-0.81)
SMB_{FF3M}	1.14***	0.90***	0.86***	0.49***	-0.15***	1.29***
	(10.5)	(15.6)	(12.8)	(4.93)	(-3.12)	(10.5)
HML_{FF3M}	0.42***	0.32***	0.08	0.20***	-0.06*	0.47***
	(4.49)	(5.70)	(1.47)	(4.00)	(-1.82)	(5.28)
			Panel C: Q-factors			
B_Q	1.01***	1.03***	0.95***	0.97***	1.04***	-0.03
	(18.0)	(40.1)	(30.6)	(25.2)	(34.9)	(-0.56)
SMB_Q	1.00***	0.70***	0.75***	0.32***	-0.11***	1.11***
	(6.63)	(6.89)	(11.8)	(3.51)	(-3.34)	(7.16)
RMW_Q	0.20	0.09	-0.16***	-0.16	-0.01	0.21
	(1.24)	(0.74)	(-2.93)	(-1.29)	(-0.30)	(1.26)
CMA_Q	0.56**	0.18	0.05	0.17	-0.01	0.57**
	(2.52)	(1.33)	(0.83)	(1.70)	(-0.31)	(2.47)
			Panel D: FF5M			
B_{FF5M}	1.00***	1.03***	0.95***	0.97***	1.04***	-0.39
	(20.0)	(39.7)	(31.7)	(24.1)	(33.2)	(-0.69)
SMB_{FF5M}	1.22***	0.91***	0.81***	0.45***	-1.15***	1.37***
	(9.15)	(14.5)	(11.8)	(4.74)	(-2.94)	(9.33)
HML_{FF5M}	0.32***	0.30***	0.09***	0.20***	-0.06**	0.38***
	(4.40)	(6.58)	(2.47)	(4.62)	(-1.99)	(4.64)
RMW_{FF5M}	0.15	0.04	-0.17***	-0.20*	0.00	0.14
	(0.96)	(0.47)	(3.25)	(-1.69)	(0.04)	(0.96)
CMA_{FF5M}	0.42**	0.04	0.01	-0.20	0.02	0.40*
	(2.11)	(0.59)	(0.10)	(1.01)	(0.52)	(1.98)

Note: Appendix 12 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by ME from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 13: Factor Loadings on Portfolio Returns Sorted by B/M

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p5 – p1)*
			Panel A: CAPM			
B_{CAPM}	0.90***	1.05***	1.15***	1.12***	1.02***	0.13*
	(30.5)	(27.8)	(27.5)	(34.7)	(18.9)	(1.67)
			Panel B: FF3M			
B_{FF3M}	0.90***	1.04***	1.15***	1.12***	1.02***	0.13**
	(35.1)	(28.7)	(27.0)	(35.8)	(22.7)	(2.05)
SMB_{FF3M}	-0.15**	0.15**	0.13	0.10	0.41***	0.57***
	(-2.12)	(2.06)	(1.22)	(1.31)	(3.79)	(3.41)
HML_{FF3M}	-0.11*	-0.08	0.02	0.05	0.37***	0.47***
	(-1.87)	(-1.46)	(0.38)	(0.91)	(5.15)	(3.98)
			Panel C: Q-factors			
B_Q	0.93***	1.04***	1.14***	1.08***	0.98***	0.05
	(29.6)	(25.1)	(27.1)	(27.1)	(18.4)	(0.66)
SMB_Q	0.01	0.16**	0.06	0.01	0.02	0.01
	(0.14)	(2.35)	(0.82)	(0.11)	(0.16)	(0.07)
RMW_Q	0.17*	-0.04	-0.08	-0.21***	-0.23	-0.40*
	(1.80)	(-0.50)	(-0.59)	(-2.79)	(-1.49)	(-1.77)
CMA_Q	0.05	-0.14*	-0.05	0.07	0.02	-0.03
	(0.78)	-1.86	(-0.49)	(0.57)	(0.16)	(-0.21)
			Panel D: FF5M			
B_{FF5M}	0.93***	1.04***	1.13***	1.08***	0.97***	0.04
	(34.0)	(25.2)	(27.4)	(27.6)	(22.5)	(0.69)
SMB_{FF5M}	-0.09	0.13*	0.10	-0.05	0.32***	0.41
	(-1.29)	(1.75)	(0.94)	(-0.69)	(2.97)	(2.53)
HML_{FF5M}	-0.15***	-0.06	0.05	0.07	0.43***	0.58***
	(-3.96)	(-1.00)	(0.77)	(1.29)	(6.61)	(6.76)
RMW_{FF5M}	0.19**	-0.05	-0.09	-0.22***	-0.30***	-0.50***
	(2.26)	(-0.38)	(-0.64)	(-2.80)	(-2.63)	(-2.85)
CMA_{FF5M}	0.11*	-0.12	-0.08	0.04	-0.17*	-0.29**
	(1.86)	(-1.51)	(-0.73)	(0.32)	(-1.67)	(-2.04)

Note: Appendix 13 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by B/M from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 14: Factor Loadings on Portfolio Returns Sorted by D/E

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p5 – p1)*
			Panel A: CAPM			
B_{CAPM}	0.97***	0.94***	0.97***	0.98***	1.07***	0.10**
	(21.3)	(28.9)	(35.0)	(40.1)	(33.3)	(2.27)
			Panel B: FF3M			
B_{FF3M}	0.97***	0.94***	0.97***	0.98***	1.07***	0.11*
	(19.6)	(31.7)	(34.7)	(39.5)	(32.6)	(2.17)
SMB_{FF3M}	0.41***	0.25***	-0.09	-0.02	0.02	-0.38***
	(4.06)	(2.84)	(-1.22)	(-0.30)	(0.30)	(-3.09)
HML_{FF3M}	0.16***	0.14***	-0.05	-0.02	0.03	-0.13**
	(3.18)	(2.99)	(-1.02)	(-0.41)	(0.77)	(-2.10)
			Panel C: Q-factors			
B_Q	0.95***	0.94***	0.96***	1.00***	1.05***	0.10*
	(18.7)	(24.4)	(29.1)	(35.8)	(33.2)	(1.78)
SMB_Q	0.31***	0.18**	-0.10	-0.01	0.00	-0.30**
	(3.03)	(2.11)	(-1.34)	(-0.14)	(0.06)	(-2.29)
RMW_Q	-0.06	0.06	-0.08	0.09	-0.10	-0.05
	(-0.63)	(0.76)	(-0.82)	(1.10)	(-1.51)	(-0.39)
CMA_Q	0.22	0.11	-0.10	-0.11*	0.15**	-0.06
	(1.69)	(1.26)	(-1.25)	(-1.74)	(2.40)	(-0.43)
			Panel D: FF5M			
B_{FF5M}	0.94***	0.94***	0.96***	1.00***	1.05***	0.10
	(17.2)	(26.5)	(29.0)	(35.5)	(32.9)	(1.72)
SMB_{FF5M}	0.40***	0.26***	-0.12	-0.01	0.01	-0.39***
	(3.83)	(2.82)	(-1.53)	(-0.15)	(0.16)	(-2.78)
HML_{FF5M}	0.14***	0.12***	-0.03	-0.00	0.01	-0.13*
	(2.72)	(2.69)	(-0.51)	(-0.07)	(0.34)	(-1.83)
RMW_{FF5M}	-0.08	0.04	-0.08	0.09	-0.11	-0.03
	(-0.90)	(0.53)	(-0.77)	(1.10)	(-1.55)	(-0.20)
CMA_{FF5M}	0.15	0.05	-0.09	-1.11	0.15**	-0.01
	(1.27)	(0.62)	(-0.97)	(-1.56)	(2.19)	(-0.04)

Note: Appendix 14 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by D/E from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 15: Factor Loadings on Portfolio Returns Sorted by CBOP

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p5 – p1)*
			Panel A: CAPM			
B_{CAPM}	1.10***	1.08***	1.12***	0.97***	0.88***	-0.22***
	(26.8)	(18.7)	(27.8)	(32.8)	(24.8)	(-3.60)
			Panel B: FF3M			
B_{FF3M}	1.10***	1.08***	1.12***	0.98***	0.88***	-0.22***
	(29.6)	(18.4)	(27.0)	(34.0)	(25.8)	(-3.82)
SMB_{FF3M}	0.35***	0.20*	-0.10	-0.05	0.01	-0.34**
	(3.31)	(1.71)	(-1.30)	(-0.92)	(0.16)	(-2.08)
HML_{FF3M}	0.16***	0.09	-0.03	0.01	-0.05	-0.21**
	(2.99)	(0.82)	(-0.75)	(0.34)	(-0.92)	(-2.26)
			Panel C: Q-factors			
B_Q	1.02***	0.92***	1.11***	1.00***	0.95***	-0.06
	(28.6)	(13.7)	(26.8)	(27.0)	(28.5)	(-1.27)
SMB_Q	0.09	-0.06	-0.10	-0.03	0.21***	0.12
	(1.05)	(-0.56)	(-1.30)	(-0.56)	(3.60)	(0.92)
RMW_Q	-0.41***	-0.78***	-0.05	0.15**	0.42***	0.83***
	(-3.54)	(-4.08)	(-0.55)	(2.15)	(6.29)	(5.26)
CMA_Q	0.07	0.25**	-0.03	-0.08	0.06	-0.00
	(0.67)	(2.22)	(-0.35)	(-0.93)	(0.96)	(-0.02)
			Panel D: FF5M			
B_{FF5M}	1.01***	0.92***	1.11***	1.01***	0.96***	-0.06
	(32.5)	(13.1)	(26.3)	(26.6)	(28.8)	(-1.31)
SMB_{FF5M}	0.24***	0.03	-0.11	-0.02	0.13**	-0.11
	(3.01)	(0.21)	(-1.36)	(-0.41)	(2.03)	(-0.93)
HML_{FF5M}	0.21***	0.13**	-0.02	0.01	-0.11***	-0.32***
	(4.54)	(2.18)	(-0.43)	(0.39)	(-3.08)	(-4.62)
RMW_{FF5M}	-0.45***	-0.80***	-0.05	0.14**	0.43***	0.88***
	(-4.88)	(-4.13)	(-0.49)	(2.08)	7.90	(7.67)
CMA_{FF5M}	-0.03	0.19*	-0.02	-0.08	0.11*	0.14
	(-0.34)	(1.69)	(-0.23)	(-0.96)	(1.77)	(1.31)

Note: Appendix 15 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by CBOP from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 16: Factor Loadings on Portfolio Returns Sorted by ARs

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p1 – p5)*
			Panel A: CAPM			
B_{CAPM}	0.99***	0.99***	1.11***	0.99***	1.04***	-0.05
	(28.2)	(20.3)	(23.4)	(30.8)	(32.4)	(-0.98)
			Panel B: FF3M			
B_{FF3M}	0.99***	0.99***	1.11***	0.98***	1.04***	-0.05
	(27.3)	(20.4)	(25.1)	(29.8)	(31.6)	(-0.99)
SMB_{FF3M}	0.10	-0.06	0.08	0.13*	0.03	0.08
	(1.54)	(-0.71)	(1.45)	(1.68)	(0.29)	(0.66)
HML_{FF3M}	0.05	-0.09**	0.09*	0.03	0.04	0.02
	(1.31)	(-2.10)	(1.86)	(0.56)	(0.71)	(0.24)
			Panel C: Q-factors			
B_{Q}	1.01***	1.03***	1.09***	0.94***	0.96***	0.05
	(31.0)	(22.6)	(22.6)	(29.8)	(21.9)	(0.92)
SMB_{Q}	0.18***	0.06	-0.03	0.04	-0.18	0.35***
	(2.69)	(0.71)	(-0.59)	(0.63)	(-1.57)	(2.72)
RMW_{Q}	0.16*	0.20**	-0.10	-0.24**	-0.43**	0.59***
	(1.72)	(2.19)	(-0.94)	(-2.58)	(-2.60)	(2.77)
CMA_{Q}	0.24***	-0.10	-0.01	0.05	-0.09	0.33*
	(2.66)	(-1.11)	(-0.07)	(0.81)	(-0.62)	(1.66)
			Panel D: FF5M			
B_{FF5M}	1.01***	1.03***	1.08***	0.94***	0.96***	0.05
	(30.8)	(22.1)	(23.6)	(29.5)	(21.5)	(0.97)
SMB_{FF5M}	0.17**	-0.01	0.05	0.08	-0.10	0.27**
	(2.31)	(-0.16)	(0.88)	(0.95)	(-1.00)	(2.01)
HML_{FF5M}	-0.01	-0.10**	0.12**	0.05	0.11	-0.12
	(-0.25)	(-2.38)	(2.19)	(1.31)	(1.41)	(-1.25)
RMW_{FF5M}	0.16*	0.21**	-0.12	-0.25**	-0.45***	0.61***
	(1.71)	(2.45)	(-1.15)	(-2.61)	(-2.86)	(2.97)
CMA_{FF5M}	0.25***	-0.05	-0.06	0.03	-0.13	0.38**
	(2.69)	(-0.91)	(-0.54)	(0.50)	(-1.02)	(2.13)

Note: Appendix 16 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by ARs from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 17: Factor Loadings on Portfolio Returns Sorted by AG2

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p1 – p5)*
			Panel A: CAPM			
B_{CAPM}	1.04***	1.06***	0.93***	1.02***	0.98***	0.06
	(21.8)	(29.5)	(24.7)	(38.0)	(20.6)	(0.80)
			Panel B: FF3M			
B_{FF3M}	1.04***	1.06***	0.93***	1.02***	0.97***	0.07
	(23.0)	(32.5)	(24.4)	(37.7)	(21.3)	(0.81)
SMB_{FF3M}	0.11	0.31***	0.12	-0.00	0.11	-0.01
	(0.99)	(3.43)	(1.51)	(-0.01)	(1.26)	(-0.04)
HML_{FF3M}	0.11*	0.12***	0.06	-0.03	0.07	0.04
	(1.85)	(2.50)	(1.20)	(-0.59)	(1.33)	(0.52)
			Panel C: Q-factors			
B_Q	0.98***	1.04***	0.95***	1.02***	0.97***	0.01
	(25.7)	(32.0)	(20.7)	(30.6)	(18.6)	(0.18)
SMB_Q	0.15*	0.26***	0.12	-0.02	-0.06	0.22*
	(1.83)	(3.48)	(1.41)	(-0.23)	(-0.75)	(1.74)
RMW_Q	-0.14	-0.06	0.15	-0.02	-0.10	-0.04
	(-1.33)	(-0.75)	(1.60)	(-0.18)	(-0.90)	(-0.25)
CMA_Q	0.66***	0.27***	-0.02	-0.12	-0.29***	0.95***
	(6.54)	(3.38)	(-0.26)	(-1.61)	(-3.93)	(6.57)
			Panel D: FF5M			
B_{FF5M}	0.98***	1.03***	0.95***	1.02***	0.97***	0.01
	(25.9)	(33.1)	(21.0)	(30.5)	(20.9)	(0.23)
SMB_{FF5M}	0.15	0.32***	0.15	-0.02	0.04	0.11
	(1.48)	(3.70)	(1.83)	(0.22)	(0.43)	(0.76)
HML_{FF5M}	-0.00	0.08	0.05	-0.00	0.15***	-0.15
	(-0.03)	(1.41)	(0.86)	(-0.01)	(3.54)	(-1.69)
RMW_{FF5M}	-0.14	-0.08	0.14	-0.02	-0.13	-0.01
	(-1.35)	(-0.99)	(1.46)	(-0.18)	(-1.29)	(-0.09)
CMA_{FF5M}	0.66***	0.23***	-0.05	-0.12	-0.36***	1.02***
	(6.42)	(2.79)	(-0.45)	(-1.56)	(-5.71)	(7.53)

Note: Appendix 17 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by AG2 from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 18: Factor Loadings on Portfolio Returns Sorted by M6,1

	Low (p1)	*p2*	*p3*	*p4*	*High (p5)*	*Hedge (p5 – p1)*
			Panel A: CAPM			
B_{CAPM}	1.12***	0.91***	0.93***	1.05***	1.07***	-0.05
	(20.1)	(15.3)	(31.0)	(19.9)	(24.5)	(-0.63)
			Panel B: FF3M			
B_{FF3M}	1.12***	0.91***	0.93***	1.05***	1.07***	-0.05
	(20.7)	(15.5)	(31.2)	(19.8)	(24.6)	(-0.66)
SMB_{FF3M}	0.06	0.23***	0.05	0.02	0.14	0.08
	(0.39)	(2.87)	(0.64)	(0.37)	(1.21)	(0.37)
HML_{FF3M}	0.10	0.01	0.04	-0.03	0.04	-0.06
	(1.27)	(0.13)	(1.05)	(-0.54)	(0.79)	(-0.57)
			Panel C: Q-factors			
B_Q	1.05***	0.94***	0.95***	1.05***	1.04***	-0.01
	(24.7)	(18.2)	(27.0)	(18.6)	(19.0)	(-0.41)
SMB_Q	-0.06	0.26***	0.04	0.02	0.04	0.09
	(-0.54)	(3.18)	(0.59)	(0.32)	(0.27)	(0.46)
RMW_Q	-0.28**	0.16*	0.09	-0.01	-0.16	0.12
	(-2.15)	(1.82)	(1.12)	(-0.12)	(-0.93)	(0.44)
CMA_Q	0.23**	-0.07	-0.01	-0.08	-0.06	-0.29
	(2.07)	(-1.06)	(-0.15)	(-0.84)	(-0.49)	(-1.59)
			Panel D: FF5M			
B_{FF5M}	1.05***	0.94***	0.95***	1.05***	1.04***	-0.02
	(23.4)	(18.1)	(27.7)	(18.5)	(19.4)	(-0.30)
SMB_{FF5M}	0.01	0.26***	0.07	0.01	0.09	0.08
	(0.05)	(3.15)	(0.84)	(0.17)	(0.61)	(0.34)
HML_{FF5M}	0.09	0.00	0.04	-0.01	0.07	-0.02
	(1.33)	(0.09)	(0.92)	(-0.19)	(1.30)	(-0.14)
RMW_{FF5M}	-0.30**	0.16*	0.08	-0.01	-0.17	0.11
	(-2.26)	(1.84)	(1.03)	(-0.09)	(-1.00)	(0.40)
CMA_{FF5M}	0.20*	-0.08	-0.03	-0.08	-0.09	-0.28
	(1.80)	(-1.03)	(-0.44)	(-0.72)	(-0.77)	(-1.59)

Note: Appendix 18 reports the factor loadings for CAPM, FF3M, the q-factor and FF5M from the monthly regressions against returns on portfolios sorted by M6,1 from July 2006 to December 2015. Numbers in parentheses represents t-stat. adjusted for the autocorrelations and heteroscedasticity. ***, ** and * indicates statistical significance at the 1% 5% and 10% levels, respectively.

APPENDIX 19: List of Sample Stocks

2006	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*
ADANA	ADANA	ADANA	ADANA	ADANA	ADANA	ADANA	ADANA	ACSEL	ACSEL
ADEL	ADEL	ADEL	ADEL	ADEL	ADEL	ADEL	ADEL	ADANA	ADANA
AEFES	AEFES	AEFES	AEFES	AEFES	AEFES	AEFES	AEFES	ADEL	ADEL
AFYON	AFYON	AFYON	AFYON	AFYON	AFYON	AFYON	AFYON	ADESE	ADESE
AKCNS	AKCNS	AKCNS	AKCNS	AKCNS	AKCNS	AKCNS	AKCNS	AEFES	AEFES
AKENR	AKENR	AKENR	AKENR	AKENR	AKENR	AKENR	AKENR	AFYON	AFYON
AKSA	AKSA	AKSA	AKSA	AKSA	AKSA	AKSA	AKSA	AKCNS	AKCNS
AKSUE	AKSUE	AKSUE	AKSUE	AKSUE	AKSUE	AKSEN	AKSEN	AKENR	AKENR
ALCAR	ALCAR	ALCAR	ALCAR	ALCAR	ALCAR	AKSUE	AKSUE	AKGUV	AKGUV
ALCTL	ALCTL	ALCTL	ALCTL	ALCTL	ALCTL	ALCAR	ALCAR	AKSA	AKPAZ
ALKA	ALKA	ALKA	ALKA	ALKA	ALKA	ALCTL	ALCTL	AKSEN	AKSA
ALKIM	ALKIM	ALKIM	ALKIM	ALKIM	ALKIM	ALKA	ALKA	AKSUE	AKSEN
ANACM	ANACM	ANACM	ANACM	ANACM	ANACM	ALKIM	ALKIM	ALCAR	AKSUE
ARCLK	ANELT	ANELT	ANELT	ANELT	ANELT	ANACM	ANACM	ALCTL	ALCAR
ARENA	ARCLK	ARCLK	ARCLK	ARCLK	ARCLK	ANELE	ANELE	ALKA	ALCTL
ARSAN	ARENA	ARENA	ARENA	ARENA	ARENA	ANELT	ANELT	ALKIM	ALKA
ASELS	ARSAN	ARMDA	ARMDA	ARMDA	ARMDA	ARCLK	ARCLK	ANACM	ALKIM
ASUZU	ASELS	ARSAN	ARSAN	ARSAN	ARSAN	ARENA	ARENA	ANELE	ANACM
ATEKS	ASUZU	ASELS	ASELS	ASELS	ASELS	ARMDA	ARMDA	ANELT	ANELE
AYCES	ATEKS	ASUZU	ASUZU	ASUZU	ASUZU	ARSAN	ARSAN	ARCLK	ANELT
AYEN	AYCES	ATEKS	ATEKS	ATEKS	ATEKS	ASELS	ASELS	ARENA	ARCLK
AYGAZ	AYEN	AYCES	AYCES	AYCES	AYCES	ASUZU	ASUZU	ARMDA	ARENA
BAGFS	AYGAZ	AYEN	AYEN	AYEN	AYEN	ATEKS	ATEKS	ARSAN	ARMDA
BAKAB	BAGFS	AYGAZ	AYGAZ	AYGAZ	AYGAZ	AYCES	AVOD	ASELS	ARSAN
BANVT	BAKAB	BAGFS	BAGFS	BAGFS	BAGFS	AYEN	AVTUR	ASUZU	ASELS
BFREN	BANVT	BAKAB	BAKAB	BAKAB	BAKAB	AYGAZ	AYCES	ATEKS	ASUZU
BOLUC	BFREN	BANVT	BANVT	BANVT	BANVT	BAGFS	AYEN	ATPET	ATEKS
BOSSA	BIMAS	BFREN	BFREN	BFREN	BFREN	BAKAB	AYGAZ	AVOD	ATPET
BRISA	BOLUC	BIMAS	BIMAS	BIMAS	BIMAS	BANVT	BAGFS	AVTUR	AVOD
BRMEN	BOSSA	BOLUC	BOLUC	BOLUC	BOLUC	BFREN	BAKAB	AYCES	AVTUR
BRSAN	BRISA	BOSSA	BOSSA	BOSSA	BOSSA	BIMAS	BANVT	AYEN	AYCES
BSOKE	BRMEN	BRISA	BRISA	BRISA	BRISA	BOLUC	BFREN	AYGAZ	AYEN
BTCIM	BRSAN	BRMEN	BRMEN	BRMEN	BRKO	BOSSA	BIMAS	BAGFS	AYES
BUCIM	BSOKE	BRSAN	BRSAN	BRSAN	BRMEN	BRISA	BIZIM	BAKAB	AYGAZ
BURCE	BTCIM	BSOKE	BSOKE	BSOKE	BRSAN	BRKO	BLCYT	BALAT	BAGFS
BURVA	BUCIM	BTCIM	BTCIM	BTCIM	BSOKE	BRMEN	BMEKS	BANVT	BAKAB
CELHA	BURCE	BUCIM	BUCIM	BUCIM	BTCIM	BRSAN	BOLUC	BASCM	BAKAN
CEMTS	BURVA	BURCE	BURCE	BURCE	BUCIM	BSOKE	BOSSA	BFREN	BALAT
CIMSA	CELHA	BURVA	BURVA	BURVA	BURCE	BTCIM	BRISA	BIMAS	BANVT
CLEBI	CEMTS	CCOLA	CCOLA	CCOLA	BURVA	BUCIM	BRKO	BIZIM	BASCM
CMBTN	CIMSA	CELHA	CELHA	CELHA	CCOLA	BURCE	BRKSN	BLCYT	BFREN
CMENT	CLEBI	CEMTS	CEMTS	CEMTS	CELHA	BURVA	BRMEN	BMEKS	BIMAS
DENCM	CMBTN	CIMSA	CIMSA	CIMSA	CEMTS	CCOLA	BRSAN	BOLUC	BIZIM
DERIM	CMENT	CLEBI	CLEBI	CLEBI	CIMSA	CELHA	BSOKE	BOSSA	BLCYT
DESA	DENCM	CMBTN	CMBTN	CMBTN	CLEBI	CEMTS	BTCIM	BRISA	BMEKS
DITAS	DERIM	CMENT	CMENT	CMENT	CMBTN	CIMSA	BUCIM	BRKO	BOLUC
DMSAS	DESA	DENCM	DENCM	DENCM	CMENT	CLEBI	BURCE	BRKSN	BOSSA
DOAS	DGZTE	DERIM	DERIM	DERIM	COMDO	CMBTN	BURVA	BRMEN	BRISA
DOBUR	DITAS	DESA	DESA	DESA	CARFA	CMENT	CCOLA	BRSAN	BRKO
EGEEN	DMSAS	DGATE	DGATE	DGATE	DENCM	COMDO	CELHA	BSOKE	BRKSN
EGGUB	DOAS	DGZTE	DGZTE	DGZTE	DERIM	CARFA	CEMAS	BTCIM	BRMEN
EGPRO	DOBUR	DITAS	DITAS	DITAS	DESA	DENCM	CEMTS	BUCIM	BRSAN
EMNIS	DURDO	DMSAS	DMSAS	DMSAS	DGATE	DERIM	CIMSA	BURCE	BSOKE
ENKAI	EGEEN	DOAS	DOAS	DOAS	DGZTE	DESA	CLEBI	BURVA	BTCIM
ERBOS	EGGUB	DOBUR	DOBUR	DOBUR	DITAS	DGATE	CMBTN	CCOLA	BUCIM
EREGL	EGPRO	DURDO	DURDO	DURDO	DMSAS	DGZTE	CMENT	CELHA	BURCE
ESCOM	EGSER	EGEEN	EGEEN	EGEEN	DOAS	DITAS	COMDO	CEMAS	BURVA
FMIZP	EMNIS	EGGUB	EGGUB	EGGUB	DOBUR	DMSAS	CARFA	CEMTS	CCOLA
FRIGO	ENKAI	EGPRO	EGPRO	EGPRO	DURDO	DOAS	DAGI	CIMSA	CELHA
FROTO	ERBOS	EGSER	EGSER	EGSER	EGEEN	DOBUR	DENCM	CLEBI	CEMAS

GENTS	EREGL	EMNIS	EMNIS	EMNIS	EGGUB	DURDO	DERIM	CMBTN	CEMTS
GEREL	ESCOM	ENKAI	ENKAI	ENKAI	EGPRO	EGEEN	DESA	CMENT	CIMSA
GOLTS	FMIZP	ERBOS	ERBOS	ERBOS	EGSER	EGGUB	DESPC	COMDO	CLEBI
GOODY	FRIGO	EREGL	EREGL	EREGL	EMNIS	EGPRO	DGATE	CARFA	CMBTN
GUBRF	FROTO	ESCOM	ESCOM	ESCOM	ENKAI	EGSER	DGZTE	DAGI	CMENT
HEKTS	GENTS	FMIZP	FMIZP	FMIZP	ERBOS	EKIZ	DITAS	DENCM	COMDO
HURGZ	GEREL	FRIGO	FRIGO	FRIGO	EREGL	EMNIS	DMSAS	DERIM	DAGI
IHEVA	GOLTS	FROTO	FROTO	FROTO	ESCOM	ENKAI	DOAS	DESA	DENCM
INDES	GOODY	GENTS	GENTS	GENTS	FMIZP	ERBOS	DOBUR	DESPC	DERIM
INTEM	GUBRF	GEREL	GEREL	GEREL	FRIGO	EREGL	DURDO	DGATE	DESA
IZMDC	HEKTS	GOLTS	GOLTS	GOLTS	FROTO	ESCOM	EGEEN	DGZTE	DESPC
IZOCM	HURGZ	GOODY	GOODY	GOODY	GENTS	FMIZP	EGGUB	DIRIT	DGATE
KAPLM	IHEVA	GUBRF	GUBRF	GUBRF	GEREL	FRIGO	EGPRO	DITAS	DGZTE
KARSN	INDES	HEKTS	HEKTS	HEKTS	GOLTS	FROTO	EGSER	DMSAS	DIRIT
KARTN	INTEM	HURGZ	HURGZ	HURGZ	GOODY	GENTS	EKIZ	DOAS	DITAS
KENT	IZMDC	IHEVA	IHEVA	IHEVA	GUBRF	GEREL	EMNIS	DOBUR	DMSAS
KIPA	IZOCM	INDES	INDES	INDES	HEKTS	GOLTS	ENKAI	DURDO	DOAS
KLMSN	KAPLM	INTEM	INTEM	INTEM	HURGZ	GOODY	ERBOS	EGEEN	DOBUR
KNFRT	KARSN	IZMDC	IZMDC	IZMDC	IHEVA	GUBRF	EREGL	EGGUB	DURDO
KONYA	KARTN	IZOCM	IZOCM	IZOCM	INDES	HEKTS	ESCOM	EGPRO	EGEEN
KORDS	KENT	KAPLM	KAPLM	KAPLM	INTEM	HURGZ	FMIZP	EGSER	EGGUB
KRSTL	KIPA	KAREL	KAREL	KAREL	IZMDC	IHEVA	FRIGO	EKIZ	EGPRO
KUTPO	KLMSN	KARSN	KARSN	KARSN	IZOCM	IHGZT	FROTO	EMNIS	EGSER
LINK	KNFRT	KARTN	KARTN	KARTN	KAPLM	INDES	GENTS	ENKAI	EKIZ
LOGO	KONYA	KENT	KENT	KENT	KAREL	INTEM	GEREL	ERBOS	EMNIS
LUKSK	KORDS	KIPA	KIPA	KIPA	KARSN	IZMDC	GOLTS	EREGL	ENKAI
MAALT	KRSTL	KLMSN	KLMSN	KLMSN	KARTN	IZOCM	GOODY	ESCOM	ERBOS
MEMSA	KUTPO	KNFRT	KNFRT	KNFRT	KENT	KAPLM	GUBRF	FMIZP	EREGL
MERKO	LINK	KONYA	KONYA	KONYA	KIPA	KAREL	HATEK	FRIGO	ESCOM
MNDRS	LOGO	KORDS	KORDS	KORDS	KLMSN	KARSN	HEKTS	FROTO	ETILR
MRDIN	LUKSK	KRSTL	KRSTL	KOZAA	KNFRT	KARTN	HURGZ	GENTS	FLAP
MRSHL	MAALT	KUTPO	KUTPO	KRSTL	KONYA	KATMR	IHEVA	GEREL	FMIZP
NETAS	MEMSA	LINK	LINK	KUTPO	KORDS	KENT	IHGZT	GOLTS	FRIGO
NTTUR	MERKO	LOGO	LOGO	LINK	KOZAA	KIPA	INDES	GOODY	FROTO
NUHCM	MNDRS	LUKSK	LUKSK	LOGO	KOZAL	KLMSN	INTEM	GUBRF	GENTS
OLMIP	MRDIN	MAALT	MAALT	LUKSK	KRSTL	KNFRT	IPEKE	HATEK	GEREL
OTKAR	MRSHL	MEMSA	MEMSA	MAALT	KUTPO	KONYA	IZMDC	HEKTS	GOLTS
PARSN	NETAS	MERKO	MERKO	MEMSA	LINK	KORDS	IZOCM	HURGZ	GOODY
PENGD	NTTUR	MNDRS	MNDRS	MERKO	LOGO	KOZAA	KAPLM	IHEVA	GUBRF
PETKM	NUHCM	MRDIN	MRDIN	MNDRS	LUKSK	KOZAL	KAREL	IHGZT	HATEK
PETUN	OLMIP	MRSHL	MRSHL	MRDIN	MAALT	KRSTL	KARSN	INDES	HEKTS
PIMAS	OTKAR	NETAS	NETAS	MRSHL	MARTI	KUTPO	KARTN	INTEM	HURGZ
PINSU	PARSN	NTTUR	NTTUR	NETAS	MEMSA	LINK	KATMR	IPEKE	IHEVA
PKART	PENGD	NUHCM	NUHCM	NTTUR	MERKO	LOGO	KENT	IZMDC	IHGZT
PKENT	PETKM	OLMIP	OLMIP	NUHCM	MGROS	LUKSK	KIPA	IZOCM	INDES
PNSUT	PETUN	OTKAR	OTKAR	OLMIP	MNDRS	MAALT	KLMSN	JANTS	INTEM
PRKAB	PIMAS	PARSN	PARSN	OTKAR	MRDIN	MARTI	KNFRT	KAPLM	IPEKE
SANKO	PINSU	PENGD	PENGD	PARSN	MRSHL	MEMSA	KONYA	KAREL	IZMDC
SARKY	PKART	PETKM	PETKM	PENGD	NETAS	MERKO	KORDS	KARSN	IZOCM
SASA	PKENT	PETUN	PETUN	PETKM	NTTUR	MGROS	KOZAA	KARTN	IZTAR
SELGD	PNSUT	PIMAS	PIMAS	PETUN	NUHCM	MNDRS	KOZAL	KATMR	JANTS
SKTAS	PRKAB	PINSU	PINSU	PIMAS	OLMIP	MRDIN	KRDMA	KENT	KAPLM
SNPAM	RYSAS	PKART	PKART	PINSU	OTKAR	MRSHL	KRSTL	KIPA	KAREL
SODA	SANKO	PKENT	PKENT	PKART	PARSN	NETAS	KUTPO	KLMSN	KARSN
SONME	SARKY	PNSUT	PNSUT	PKENT	PENGD	NTTUR	LINK	KNFRT	KARTN
TATGD	SASA	PRKAB	PRKAB	PNSUT	PETKM	NUHCM	LKMNH	KONYA	KATMR
TEKTU	SELGD	RYSAS	RYSAS	PRKAB	PETUN	OLMIP	LOGO	KORDS	KENT
THYAO	SKTAS	SANKO	SANKO	RYSAS	PIMAS	OTKAR	LUKSK	KOZAA	KIPA
TIRE	SNPAM	SARKY	SARKY	SANKO	PINSU	PARSN	MAALT	KOZAL	KLMSN
TOASO	SODA	SASA	SASA	SARKY	PKART	PENGD	MARTI	KRDMA	KNFRT
TRCAS	SONME	SELEC	SELEC	SASA	PKENT	PETKM	MEMSA	KRONT	KONYA
TRKCM	TATGD	SELGD	SELGD	SELEC	PNSUT	PETUN	MERKO	KRSAN	KORDS
TTRAK	TCELL	SILVR	SILVR	SELGD	PRKAB	PIMAS	MGROS	KRSTL	KRDMA

TUKAS	TEKTU	SKTAS	SKTAS	SILVR	RYSAS	PINSU	MNDRS	KUTPO	KRONT
TUPRS	THYAO	SNPAM	SNPAM	SKTAS	SANKO	PKART	MRDIN	KUYAS	KRSAN
ULKER	TIRE	SODA	SODA	SNPAM	SARKY	PKENT	MRSHL	LINK	KRSTL
UNYEC	TOASO	SONME	SONME	SODA	SASA	PNSUT	NETAS	LKMNH	KUTPO
USAK	TRCAS	TATGD	TATGD	SONME	SELEC	PRKAB	NTTUR	LOGO	KUYAS
VAKKO	TRKCM	TCELL	TCELL	TATGD	SELGD	PRKME	NUHCM	LUKSK	LINK
VESTL	TTRAK	TEKTU	TEKTU	TCELL	SILVR	RYSAS	OLMIP	MAALT	LKMNH
VKING	TUKAS	THYAO	THYAO	TEKTU	SKTAS	SANKO	OTKAR	MARTI	LOGO
YATAS	TUPRS	TIRE	TIRE	THYAO	SNPAM	SARKY	PARSN	MEGAP	LUKSK
YUNSA	ULKER	TOASO	TOASO	TIRE	SODA	SASA	PENGD	MEMSA	MAALT
	UNYEC	TRCAS	TRCAS	TOASO	SONME	SELEC	PETKM	MEPET	MARTI
	USAK	TRKCM	TRKCM	TRCAS	TATGD	SELGD	PETUN	MERKO	MEGAP
	VAKKO	TTRAK	TTRAK	TRKCM	TCELL	SILVR	PIMAS	MGROS	MEPET
	VESTL	TUKAS	TUKAS	TTKOM	TEKTU	SKTAS	PINSU	MNDRS	MERKO
	VKING	TUPRS	TUPRS	TTRAK	THYAO	SNPAM	PKART	MRDIN	MGROS
	YATAS	ULKER	ULKER	TUKAS	TIRE	SODA	PKENT	MRSHL	MNDRS
	YUNSA	UNYEC	UNYEC	TUPRS	TOASO	SONME	PNSUT	NETAS	MRDIN
		USAK	USAK	ULKER	TRCAS	TATGD	PRKAB	NTTUR	MRSHL
		VAKKO	VAKKO	UNYEC	TRKCM	TCELL	PRKME	NUHCM	NETAS
		VESBE	VESBE	USAK	TTKOM	TEKTU	RYSAS	OLMIP	NIBAS
		VESTL	VESTL	VAKKO	TTRAK	THYAO	SAMAT	OTKAR	NTTUR
		VKING	VKING	VESBE	TUKAS	TIRE	SANKO	OYLUM	NUHCM
		YATAS	YATAS	VESTL	TUPRS	TOASO	SARKY	OZBAL	ODAS
		YUNSA	YUNSA	VKING	ULKER	TRCAS	SASA	PARSN	OLMIP
				YATAS	UNYEC	TRKCM	SELEC	PENGD	ORMA
				YUNSA	USAK	TTKOM	SELGD	PETKM	OTKAR
					VAKKO	TTRAK	SILVR	PETUN	OYLUM
					VESBE	TUKAS	SKTAS	PIMAS	OZBAL
					VESTL	TUPRS	SNPAM	PINSU	PARSN
					VKING	ULKER	SODA	PKART	PENGD
					YATAS	UNYEC	SONME	PKENT	PETKM
					YUNSA	USAK	TATGD	PNSUT	PETUN
						VAKKO	TCELL	PRKAB	PIMAS
						VESBE	TEKTU	PRKME	PINSU
						VESTL	THYAO	PRZMA	PKART
						VKING	TIRE	RYSAS	PKENT
						YATAS	TOASO	SAMAT	PNSUT
						YUNSA	TRCAS	SANFM	PRKAB
							TRKCM	SANKO	PRKME
							TTKOM	SARKY	PRZMA
							TTRAK	SASA	ROYAL
							TUKAS	SELEC	RYSAS
							TUPRS	SELGD	SAMAT
							ULKER	SILVR	SANFM
							UNYEC	SKTAS	SANKO
							USAK	SNPAM	SARKY
							VAKKO	SODA	SASA
							VESBE	SONME	SAYAS
							VESTL	TATGD	SELEC
							VKING	TCELL	SELGD
							YATAS	TEKTU	SILVR
							YUNSA	THYAO	SKTAS
								TIRE	SNPAM
								TKNSA	SODA
								TOASO	SONME
								TRCAS	TATGD
								TRKCM	TCELL
								TTKOM	TEKTU
								TTRAK	THYAO
								TUKAS	TIRE
								TUPRS	TKNSA
								ULKER	TMSN
								UNYEC	TOASO

USAK	TRCAS
VAKKO	TRKCM
VESBE	TTKOM
VESTL	TTRAK
VKING	TUKAS
YATAS	TUPRS
YUNSA	ULAS
	ULKER
	UNYEC
	USAK
	VAKKO
	VESBE
	VESTL
	VKING
	YATAS
	YAYLA
	YUNSA
	YYAPI