MISPRICING in BORSA ISTANBUL STOCK RETURNS

A Thesis

by

Adnan Çağrı Demir

Submitted to the
Graduate School of Sciences and Engineering
In Partial Fulfillment of the Requirements for
the Degree of

Master of Science

in the
Financial Engineering

Özyeğin University
September 2018

MISPRICING in BORSA ISTANBUL STOCK RETURNS

Approved by:

Dr. Biliana Guner, Advisor,
Department of Finance
Özyeğin University

Associate Professor Atakan Yalçın,
Department of Finance
Özyeğin University

Associate Professor Yiğit Atılgan,
School of Management
Sabanci University

Date Approved: 17 September 2018

To my loves Nazan and Tuna…

ABSTRACT

Stock return anomalies literature has been boosted in the last decade and the number of “anomaly factors” detected has increased dramatically which was described by Cochrane (2011) as “factor zoo”. We investigated the existence of 9 stock return anomalies in Borsa Istanbul which have been survived extensive investigations in US-based literature. We found out gross profitability, return-on-asset, and composite equity issues anomalies also observed in BIST whereas asset growth and accruals anomalies work in the opposite direction compared to U.S studies. Next, by combining significant anomalies and momentum, we construct a single mispricing factor which works better than each individual anomaly in terms of anomalous behavior. Moreover, we propose a four-factor asset pricing model by utilizing the mispricing factor with market, value, and size factors. The p-value for the Gibbons-Ross-Shanken (1989)'s test that all anomalies' alphas are jointly equal to zero is 0.08 for our model and 0.016 for Fama French 3-factor model. That is, our model captures better the systematic drivers of returns in BIST.

ÖZET

Hisse senedi getiri anomalileri literatürü son 10 yılda aşırı büyüme göstermiş ve tespit edilen anomali faktörü sayısı önemli oranda artmıştır. Öyle ki Cochrane (2011) bu durumu "factor hayvanat bahçesi"ne benzetmektedir. Çalışmamızda, ABD temelli yapılan araştırmalarda detaylıca incelenmiş olan 9 anomaliyi Borsa İstanbul hisse getirileri için inceledik. Brüt kar, aktif karlılık, kompozit hisse senedi ihracı anomalilerinin Bist'te de var olduğunu; varlık büyümesi ve tahakkuklar anomalilerinin ise ABD piyasalarına yönelik calışmalardaki bulgularla aksi yönde işlediğini tespit ettik. İstatistiksel olarak anlamlı anomalileri ve momentum anomalisini kullanarak olusturduğumuz kompozit yanlış fiyatlandırma ölçütünün herbir anomaliden kayda deger biçimde daha anormal olduğunu ortaya koyduk. Yanlış fiyatlandırma ölçütü ile piyasa, değer, ve büyüklük faktörlerini birleştirerek dört faktörlü bir finansal varlık fiyatlandırma modeli tasarladık. Bütün anomali alfalarının aynı anda sıfır olma ihtimalini ölçen Gibbons-Ross-Schanken p-değeri bizim modelimiz için 0.08 iken aynı dğer Fama French 3-faktörlü model için 0.016'dır. Yani, tasarladığımız model BIST'te sistematik getiri faktörlerini daha iyi tespit etmektedir.

ACKNOWLEDGMENTS

This thesis would never have been possible without all the support, inspiration and encouragement from my close surroundings. Among many people who have supported me during my research work, there are some particular persons I would like to take the opportunity to express my gratitude: First and foremost, I offer my sincerest thanks to my supervisor Dr. Biliana Guner who understood my curiosity and was always there whenever I needed her guidance. I lack in words to show my gratitude for her motivation, cooperation, and guidance I shall be indebted to her all through my life.

I would also like to thank the other members of my oral defense committee; Associate Professors Atakan Yalçın and Yiğit Atilgan for their time and insightful questions.

No thanks can adequately repay the gracious help and hearted cooperation rendered by my friend Kaan Kocak who motivated and accelerated me whenever I felt low, and also kept me smiling during my studies.

I would never forget my family members without them, this work is not easily possible for me and they gave me spiritual and moral support. My deepest gratitude goes to my wife Nazan for her unflagging love and support. She took all the pains to make it possible for me to complete the work by keeping me away from all the sorrows of the life. No words would be enough to express my feelings towards my son Ahmet Tuna, for cheering me with love and affection and making my life so colorful during the course of my work.

Finally, I would like to thank those who directly or indirectly, knowing or unknowing helped me to finish my work. Nevertheless, any errors are my own and should not tarnish the reputations of these esteemed persons.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION and PREVIOUS LITERATURE

Last decade witnessed a huge increase in the number of asset pricing anomalies investigated in the anomaly literature also known as “factors”. Harvey et al. (2015) mentions over 300 factors that were “discovered” and published in a selection of journals by 2012. Hou et. al. (2017) puts together a large library of anomalies by gathering around 450 of them and indicates that 85% of the anomalies they compiled are insignificant at the cutoff T-statistic of three. With unpublished and working papers, the real number is arguably higher than that figure. This extensive investigation rises data mining and p-hacking concerns. Cochrane (2011) points out this issue: “to address these questions in the zoo of new variables, I suspect we will have to use different methods.” To overcome this issue academic literature has developed new statistical methods and propose new statistical cut-offs, such as Harvey et al. (2016), McLean and Pontiff (2016), Green et al. (2017), Barillas and Shanken (2018).

Using a low-dimensional asset pricing model to explain the cross-section of stock returns is a common approach in the literature. The most prominent such model is Fama and French (1993) 's three-factor model, in which a market factor is combined with a value and a size factor. Carhart (1997) extends FF3 by adding a momentum factor. More recently, Fama and French (2015) added an investment factor and a profitability factor to their three-factor model, thus formulating a five-factor model (FF5). Hou et al. (2014) argues that a four-factor model, consisting of the market factor,

a size factor, an investment factor, and a profitability factor, generally explains the cross-section of stock returns and outperforms FF3.

Identifying a legitimate factor is of great importance because empirical factor models are used to assess investment performance and risk. Every portfolio is exposed to at least some of risk factors. To construct a factor, a common approach is to rank stocks according to a single anomaly variable, such as B/M. However, a single proxy can be more prone to be affected by irrelevant factors or economic conditions. That is, a single variable can be a very noisy proxy for the targeted factor. To sum up, trying to explain as many systematic drivers of returns as possible and using more stable proxies to construct factors are among the main hurdles that a factor model needs to overcome.

Stambaugh and Yuan (2016) handle this issue in a way different from the above-mentioned models. Instead of using a single variable for an anomaly factor as a proxy, they average stock rankings across multiple anomaly proxies. This way they get a less noisy measure of a stocks' mispricing. They use 11 prominent stock return anomalies to construct two mispricing factors and argue that their model, consisting of market, size, and their two mispricing factors, performs better than the Fama French five-factor model and the four-factor model of Hou et al. (2015a). The most distinct characteristic of Stambaugh and Yuan (2016)'s approach is that it captures the different aspects of a larger set of anomalies simultaneously.

Following Stambaugh and Yuan (2016), we investigated 9 prominent anomalies in the Borsa Istanbul (BIST) stock returns. Because of the lack of research on mispricing and anomalies on BIST, instead of assuming the existence of those anomalies and directly jumping to the construction of the mispricing factor, our study starts with an investigation of the existence of those 10 anomalies. We find that

anomalies related to profitability (gross profitability and return-on-asset) and stock issuance (composite equity issuance) are the strongest anomalies for BIST. The asset growth anomaly works in the opposite direction than it works in US markets. The difference between value-weighted and equally-weighted portfolio analysis implies that most anomalies show different behaviors across firm sizes.

After analyzing the individual anomalies, we propose a four-factor model for BIST stock returns. First, to construct a composite mispricing measure, we use the five significant anomalies, together with momentum. We use that mispricing measure to construct the new risk factor, which we add to market, size, and value to form the four-factor model. We show that our factor model outperforms FF3 in explaining the anomalies used to construct the composite mispricing measure. The p-value for the Gibbons-Ross-Shanken (1989)'s test that all anomalies' alphas are jointly equal to zero is 0.08 for our model and 0.016 for FF3. That is, our model captures better the systematic drivers of returns in BIST.

CHAPTER II

DATA DESCRIPTION and MISPRICING PROXIES

Data for the analysis are obtained from several sources. Stock returns, market capitalizations, book to market ratios, and annual market constituents are obtained from Borsa Istanbul. Accounting data used to construct anomaly proxies come from Bloomberg Terminal. Stock issuance data is obtained from StockGround. Our sample period is from January 2003 to December 2016. For accounting data, the variable names and frequencies are indicated and discussed under the individual anomaly proxies' subsection. In case the data start before 2003 for an anomaly, the portfolio construction strategies are implemented in such a way that portfolio returns are first observed in January 2003.

2.1 Market Constituents

All Borsa Istanbul Equity Markets stock lists are provided by Borsa Istanbul. To be included in the analysis, a stock should be traded in National Market, Second National Market, Bist Main, or Bist Star Markets at Borsa Istanbul[1]. For this purpose, only the stocks that are listed in one of the main markets on the last trading day of year t-1 are included in the analysis for year t. Market lists are updated annually. REIT's are cleaned from all calculations. Only the common shares are included. Unless otherwise stated, all data is for the period from December 31, 2002 to December 31, 2016.

[1] Borsa Istanbul (Istanbul Menkul Kiymetler Borsasi – IMKB until April 2013) market segmentation had experienced several amendments in the sample period. We included two main markets, National and Second National market, until 2014 and Bist Star and Bist Main markets after 2014.

2.2 Price and Market Capitalization Data

Monthly stock returns and market capitalizations are obtained from Borsa Istanbul. Both stock returns and market capitalization of firms filtered based on:

1. Return filter: To account for the stock splits, mergers, and dividends which are not identifiable, returns falling beyond 0.1 and 99.9 percentiles are set to be missing.

2. Market capitalization filter: Ince and Porter (2003) suggest that price-related errors are concentrated among penny stocks. To make results robust to penny stocks, at each portfolio formation month, we exclude stocks whose market capitalization is below the 10th percentile in that month.

2.3 Factor Construction

The three Fama-French factors are calculated as in Fama and French (1993). More specifically:

1. Market: Market's return series is calculated as the value-weighted average of all stocks that passed the return and market capitalization filters.

2. Risk-free rate: Risk-free rate is calculated from monthly values of BIST GDS 91 Days index[2].

3. HML and SMB (FF3): Annual year-end price-to-book ratios are obtained Borsa Istanbul. HML and SMB factors are calculated in the manner explained in Fama and

[2] BIST GDS indices are calculated by BIST and measure the zero-coupon and fixed-rate coupon Turkish Government Debt Securities issued in Turkish Lira and traded in BIST for several maturity bands. Further information can be found on www.borsaistanbul.com.

French (1993). Stocks with negative price-to-book ratios are excluded from calculations.

2.4 Anomaly Proxies and Portfolio Construction

To ensure availability of accounting data, we make sure there are at least four months between the month accounting data are observed and portfolio formation month. For instance, for annual data, the portfolios are formed at the end of April of year t, and portfolio returns are observed in May of year t. Portfolios formed earlier than April (e.g., January to March of year t) use annual data observed in December of year t-2. Because of the limited number of stocks, each month we sort stocks into quintiles. That is, the most (least) underpriced stocks according to each anomaly are put in the first (fifth) portfolio. For the monthly portfolio returns to be calculated, each month each quintile portfolio is expected to have at least 10 stocks for that month[3].

The direction of the "a priori" under- (over-) pricing is determined based on the evidence in the original U.S-market-based studies that first uncover the respective anomalies. However, for the BIST stock returns, some of the anomalies turn out to be insignificant, while others seem to be reversed, as explained below. Conversely, it is possible that there are BIST-specific anomalies that are not present in U.S. stock market returns. Such anomalies (if existing) remain out of the scope of our study. Including them can only be expected to strengthen the performance of our four-factor model. The existence and strength of anomalies are analyzed by examining the return of the spread portfolio, consisting of a long position in the most underpriced stocks (portfolio 1) and a

[3] The number of stocks in each quintile ranges from 11 in July, August, and September 2004 for Investment anomaly to 63 in January 2013 for Momentum anomaly. Figure 1 in the Appendix presesents the evolution of minimum and average stock numbers per quintile through sample period across anomalies.

short position in the least underpriced (or overpriced) stocks (portfolio 5). For each such spread portfolio, we are interested in the sign and statistical significance of the sample mean return, as well as the risk-adjusted mean return (the alpha from the FF3 model).

Below, we define the anomaly proxies, as well as the control variables we use in our empirical analysis. The anomaly proxies are the ones used by Stambaugh and Yuan (2016).

1. Momentum (MOM): Jegadeesh and Titman (1993) shows that momentum anomaly is significant for certain windows of periods in the US. The momentum anomaly measure is calculated as cumulative return from month t-6 to t-2 at the end of month t-1. Here, portfolios are constructed at the end of month t-1 and portfolio returns are observed at month t. High (low) momentum stocks are expected to have high future returns.

2. Asset Growth (AG): Following Cooper et al. (2008), asset growth anomaly measure is the growth of total assets. Asset growth in quarter t is defined as, total assets at the end of quarter t-1 minus total assets at the end of quarter t-2 divided by total assets at the end of quarter t-2. Asset growth is negatively related to expected stock returns.

3. Gross Profitability (GP): Novy-Marx (2013) shows that higher profitability firms have higher returns than lower profitability firms. He asserts that gross profit is the cleanest measure of profitability. Gross profitability anomaly measure is calculated as the quarterly gross profit divided by the same quarter's end of quarter total assets. Gross profit is defined as the total revenue minus cost of goods sold. Following Lu et al. (2018), We delete gross profitability measure observations higher than 1 and less than -1.

4. Return-on-Assets (ROA): Fama and French (2006) and Chen, Novy-Marx, and Zhang (2010) show that firms with higher return on assets tend to earn abnormally

higher subsequent returns. ROA is calculated as the quarterly net income over one-quarter-lagged end of quarter total assets.

5. Investment to assets (INV): Titman, Wei, and Xie (2004) find that investment is a proxy for lower future returns. That is, high investment firms tend to generate low future returns. Investment-to-assets proxy is calculated as the quarterly change in gross property, plant and, equipment plus the quarterly change in inventory divided by the lagged value of end of quarter total assets.

6. Accruals Anomaly (ACCR): Following Sloan (1996), the accruals anomaly proxy is calculated as the annual change in noncash working capital minus depreciation and amortization expense, divided by annual total assets. The proxy variable is calculated quarterly. Accruals is negatively related to expected returns.

7. Net Operating Assets (NOA): Hirshleifer, Hou, Teoh, and Zhang (2004) assert that investors underestimate the importance of cash profitability and focuses on accounting profitability. Net operating assets can be seen as the cumulative difference between operating income and free cash flow. Thus, net operating assets is a proxy for such bias. NOA is computed as annual year-end net operating assets divided by the lagged value of annual year-end total assets. Like ACCR, high NOA firms tend to earn abnormally low future returns.

8. Composite Equity Issues (CEI): Composite equity issues is defined by Daniel and Titman (2006) as the difference between cumulative 12-month growth in market capitalization minus 12-month cumulative stock return. The proxy can be interpreted as the change in market capitalization that does not stem from price change. Composite equity issues measure is negatively related to expected returns.

9. Ohlson's O-score (OSCR): O-score is a financial distress measure proposed by Ohlson (1980). It shows how likely it is for a company to go bankrupt. The coefficients for the score calculation are estimated by a static probit model. Begley et al. (1996) expresses that O-score proxies the financial distress better when the model is re-estimated by using recent accounting data. Therefore, we used coefficients re-estimated by Oz and Yelkenci (2015) for the Turkish stock market:

$$O-score = -1.34 - 1.21 \cdot SIZE - 0.45 \cdot TLTA - 2.13 \cdot WCTA + 0.01 \cdot CLCA - 0.30 \cdot ROA + 0.00 \cdot OCFTA - 1.05 \cdot ONEG + 1.09 \cdot CHIN,$$

where SIZE is the log of total assets, TLTA is total liabilities divided by total assets, WCTA is working capital, CLCA is current liabilities divided by current assets, ROA is net income divided by total assets, OCFTA is cash flow from operations divided by total assets, ONEEG is 1 if total liabilities exceed total assets and is zero otherwise, CHIN is $(NI_j - NI_{j-1}) / (|NI_j| + |NI_{j-1}|)$, in which NI_j is the income for year j, which is the most recent reporting year that ends at least four months before the end of month t-1. Since the accounting data for O-score calculations is not enough to form portfolios for some months, OSCR covers the period from August 2005 to December 2016. P

2.5 Control Variables

Beta: We estimated beta from the market model below by a rolling regression approach:

$$r_{i,t} = \alpha_{i,t} + beta_{i,t} \cdot Market_t + \epsilon_{i,t}$$

where $r_{i,t}$ is the excess return of stock i at month t and $Market$ is the value-weighted average of all stocks which passed price and market capitalization' filters. Rolling window is 36 months and a firm should have at least 20 months of the return observations in the preceding 36 months to be included in the beta estimation

calculation. Given the window length, first beta is calculated for the month of August 2003.

B/M: Annual year-end book-to-market is the same ratio as the one used to calculate the HML factor.

Size: Size is the log of annual year-end market capitalization.

Illiq: We utilized Amihud (2002) illiquidity measure as the illiquidity control variable. Illiq is the monthly average of the ratio of the daily absolute return to the daily trading volume in local currency (Turkish Lira) for each stock.

2.6 Composite Mispricing Measure

For each anomaly, all available stocks are ranked according to the respective anomaly proxy variable assigning the highest rank to the most underpriced stock. That is, the stocks with the highest (lowest) expected returns get the highest (lowest) rank. The Composite measure for stock i in month t, $COMP_{i,t}$, is calculated as the average rank of stock i at time t across all anomalies that are significant for BIST equity returns plus momentum. As we will discuss in Section 3.1, the significant anomalies are asset growth, gross profitability, return-on-assets, accruals, and composite equity issues. Since AG and ACCR turn out to be working in the opposite direction compared to the US evidence, the AG and ACCR proxy rankings reflect the de facto relation in BIST. Ranks are scaled to 0-100 range. The mispricing ranking is a relative measure and reflects the cross-sectional mispricing ranking each month. Therefore, the scaled rank for an individual stock and a given anomaly can be seen like a mispricing grade where 100 is assigned to the stocks that are most underpriced relative to the other stocks at

time t and, accordingly, have the highest expected returns. For COMPi,t to be calculated, stock i must have at least three valid ranking grades at time t.

To evaluate the relationship between Comp and expected returns, we perform univariate portfolio analysis, using Comp as the sorting variable. The spread portfolio is constructed, as before, by going long in the most underpriced stocks (highest Comp value) and short in the most overpriced stocks (lowest Comp value). Significance of an individual anomaly is decided according to single-sort sample portfolio spreads t-stats.

2.7 Descriptive Statistics

Table 1 Panel A reports return and control variable statistics as time series means of cross-sectional characteristics. The overall sample has 56,826 firm-month observations. Average of monthly cross-sectional stock returns is 2% with a standard deviation of 7.66%. Firms in the sample period have an average size of 1096.98 million Turkish Lira. The mean and the median of the cross-sectional average of stock betas are both 0.9. Average B/M is 0.92. Average absolute price change per millions of Turkish Lira of trading volume is 13.42%.

Table 1

Summary statistics. Panel A reports summary characteristics and return statistics for the stocks in the sample. The sample period is from January 2003 to December 2016. Size is market capitalization (in million Turkish Lira), B/M is book-to-market ratio, Beta is market beta, computed from the market model, Illiq is the Amihud (2002) illiquidity measure. Panel B reports time-series averages of monthly cross-sectional median anomaly proxies.

Panel A: Descriptive return and control variables statistics

	Mean	Median	SD	Skewness	Kurtosis
Average Return (%)	2.00	1.81	7.66	1.59	5.33
Size	1096.98	1218.82	432.45	-0.49	-1.01
Beta	0.90	0.90	0.07	-0.25	-0.41
B/M	0.92	0.89	0.31	1.70	4.46
Illiq (%)	13.42	1.07	22.75	2.45	6.87

Panel B: Time-series average of median proxy variables

Anomaly	Average	Standard Deviation
Momentum	0.05	0.35
Asset Growth Anomaly	0.02	0.20
Gross Profitability Anomaly	0.04	0.04
Return-on-Asset Anomaly	0.01	0.03
Investment Anomaly	0.02	0.18
Accruals Anomaly	-0.01	0.07
Net Operating Assets Anomaly	0.73	0.33
Composite Equity Issues Anomaly	0.00	6.87
Ohlson’s O-score	-0.06	2.05

CHAPTERS III

PORTFOLIO and FAMA-MACBETH ANALYSIS

In this section, we discuss single portfolio sorts of stocks based on individual anomaly proxies and investigate the robustness of the anomalies suing double independent portfolio sorts, and Fama-MacBeth regression analysis results. The section concludes with the examination of the composite mispricing measure analysis.

3.1 Single Portfolio Sorts

At the end of each month t, portfolios are constructed according to the corresponding proxy variables and rebalanced according to the proxy variables frequency, as discussed in Section 2.4. Next, for each quintile, we obtain time-series of both equally-weighted (EW) and value-weighted (VW) portfolio returns. We then calculate spreads of EW and VW portfolio returns of the extreme portfolios. Table 2 reports the sample means and the risk-adjusted average spread portfolio returns. We use FF3 to estimate alphas.

As Atilgan et al. (2016) and Alkan and Guner (2018) suggest, the mean spread between VW momentum portfolios is more like a reversal and is not significant with a mean -0.34% and T-stat of -0.60. However, EW momentum spread is significant at the 10% level (mean spread 0.58%, t-stat 1.76). This result evokes the Carhart (1997)'s strategy of constructing momentum factor from EW portfolios. The two profitability anomalies (gross profitability anomaly and return-on-asset anomaly) generate similar results (mean spreads are 0.82%, 0.81%, and T-stats are 3.42, 2.97 for GP and ROA,

respectively). They are both stronger in the EW portfolios than the VW case. Both EW and VW mean returns are positive.

Composite equity issues (CEI) is a proxy for equity issuance. Atilgan et al. (2016) argue that when controlled for other factors, equity issuance has strong negative relation with expected stock returns in BIST. Our results support their findings. All portfolio spreads are positive for CEI (mean spreads are 1.02% and 0.54%, for EW and VW case, respectively). Equally weighted portfolios spread is statistically strongly significant (T-stat 4.32). VW portfolio spreads are not significant despite being positive (T-stat 1.5).

The asset growth anomaly generates negative and significant spreads for both VW and EW portfolios (mean spreads are -0.76%, -0.95% and T-stats are -2.90, -2.51 for EW and VW spreads, respectively). Since portfolio sorts are performed using the proxy-expected return relationship established for the US equity market, having a negative sign of mean spread return means that asset growth is positively related to future returns for BIST equities and works in the opposite direction compared to US evidence. Another interesting anomaly finding belongs to the accruals anomaly. Our results show that accruals anomaly also works in the reverse direction than it works for US markets. Moreover, the results are significant at 10% level for VW and EW portfolio spreads of accruals anomaly (mean spreads are -0.52 and -0.53, T-stats are -1.90 and -1.67 for EW and VW case, respectively).

When it comes to the investment anomaly, despite it being an economically close anomaly to asset growth anomaly for US markets, evidence is neither significant nor consistent across portfolio construction structures (T-stats are -1.22 and 0.57 for

EW and VW portfolio spreads, respectively). Both net operating assets and O-score produce insignificant average sample spreads across equally and VW portfolios.

Table 2

Univariate sorts. Entries in the table are average value- and equally-weighted returns of portfolios sorted on the basis of anomaly proxies. At the end of each month t, stocks are sorted into decile portfolios according to proxies within month t. Portfolios are rebalanced according to proxy frequency. The FF3 alphas are based on a three-factor model in which portfolio returns are regressed on Market, value, and size. The spread portfolios are formed by a long position in the most underpriced portfolio and a short position in most the overpriced portfolio. T-statistics, based on Newey-West adjusted standard errors, are reported in brackets.

Momentum				
	Equally-Weighted		**Value-Weighted**	
Quintile	**Average Excess Return (%)**	**FF3 Alpha (%)**	**Average Excess Return (%)**	**FF3 Alpha (%)**
High Momentum	0.73	0.08	0.37	-0.22
2	1.14	0.42	0.47	-0.13
3	0.84	0.25	0.21	-0.20
4	0.68	0.08	0.67	0.34
Low Momentum	0.15	-0.47	0.70	0.33
High MOM - Low MOM	0.58	0.56	-0.34	-0.55
	(1.76)	(1.64)	(-0.60)	(-0.94)

Asset Growth				
	Equally-Weighted		**Value-Weighted**	
Quintile	**Average Excess Return (%)**	**FF3 Alpha (%)**	**Average Excess Return (%)**	**FF3 Alpha (%)**
Low AG	0.22	-0.34	-0.11	-0.66
2	0.60	-0.04	0.01	-0.43
3	0.69	0.05	0.79	0.11
4	0.64	-0.04	0.39	-0.12
High AG	0.98	0.34	0.83	0.28
Low AG - High AG	-0.76	-0.68	-0.95	-0.95
	(-3.36)	(-2.90)	(-2.58)	(-2.51)

Gross Profitability				
	Equally-Weighted		Value-Weighted	
Quintile	Average Excess Return (%)	FF3 Alpha (%)	Average Excess Return (%)	FF3 Alpha (%)
High GP	1.03	0.51	0.50	0.09
2	0.81	0.18	0.39	-0.15
3	0.71	0.10	0.90	0.41
4	0.41	-0.23	0.45	-0.21
Low GP	0.21	-0.55	-0.05	-0.84
High GP - Low GP	0.82	1.06	0.55	0.92
	(3.42)	(4.36)	(1.50)	(2.59)

Return-on-Asset				
	Equally-Weighted		Value-Weighted	
Quintile	Average Excess Return (%)	FF3 Alpha (%)	Average Excess Return (%)	FF3 Alpha (%)
High ROA	1.10	0.50	0.48	0.12
2	0.95	0.29	0.72	0.14
3	0.75	0.08	0.71	0.10
4	0.16	-0.48	0.08	-0.66
Low ROA	0.30	-0.26	-0.32	-0.78
High ROA - Low ROA	0.81	0.76	0.80	0.89
	(2.97)	(2.81)	(1.93)	(2.14)

Investment				
	Equally-Weighted		Value-Weighted	
Quintile	Average Excess Return (%)	FF3 Alpha (%)	Average Excess Return (%)	FF3 Alpha (%)
Low INV	0.57	-0.08	0.55	0.02
2	0.30	-0.35	0.27	-0.21
3	0.84	0.24	0.57	-0.06
4	0.71	0.01	0.60	-0.15
High INV	0.85	0.23	0.37	-0.11
Low INV - High INV	-0.29	-0.31	0.18	0.13
	(-1.22)	(-1.26)	(0.47)	(0.32)

Accruals				
	Equally-Weighted		Value-Weighted	
Quintile	**Average Excess Return (%)**	**FF3 Alpha (%)**	**Average Excess Return (%)**	**FF3 Alpha (%)**
Low ACCR	0.00	0.00	0.00	0.00
2	0.01	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00
4	0.00	0.00	0.01	0.00
High ACCR	0.01	0.00	0.01	0.00
Low ACCR - High ACCR	-0.52	-0.51	-0.70	-0.53
	(-1.99)	(-1.88)	(-1.67)	(-1.22)

Net Operating Assets				
	Equally-Weighted		Value-Weighted	
Quintile	**Average Excess Return (%)**	**FF3 Alpha (%)**	**Average Excess Return (%)**	**FF3 Alpha (%)**
Low NOA	0.55	-0.04	0.48	-0.04
2	0.80	0.21	0.56	0.11
3	0.45	-0.18	0.45	-0.08
4	0.65	-0.06	0.62	-0.12
High NOA	0.76	0.08	0.11	-0.44
Low NOA - High NOA	-0.21	-0.12	0.37	0.39
	(-0.96)	(-0.53)	(0.99)	(1.00)

Composite Equity Issues				
	Equally-Weighted		Value-Weighted	
Quintile	**Average Excess Return (%)**	**FF3 Alpha (%)**	**Average Excess Return (%)**	**FF3 Alpha (%)**
Low CEI	1.19	0.58	0.60	0.17
2	0.76	0.11	0.62	0.09
3	0.77	0.19	0.56	0.09
4	0.61	-0.07	0.40	-0.18
High CEI	0.17	-0.48	0.05	-0.49
Low CEI - High CEI	1.02	1.06	0.54	0.66
	(4.32)	(4.49)	(1.50)	(1.83)

O-Score				
	Equally-Weighted		Value-Weighted	
Quintile	Average Excess Return (%)	FF3 Alpha (%)	Average Excess Return (%)	FF3 Alpha (%)
Low OSCR	0.41	-0.22	0.46	-0.29
2	0.90	0.25	0.48	-0.11
3	0.74	0.03	0.36	-0.18
4	0.72	0.20	0.49	0.13
High OSCR	0.63	-0.01	0.47	-0.29
Low OSCR - High OSCR	-0.22	-0.22	-0.01	0.00
	(-0.97)	(-0.92)	(-0.02)	(0.00)

Figure 1 reports the correlations between EW anomaly portfolio spreads. We observe that the highest correlation over the sample period is 0.49 and it is between gross profitability and return-on-assets EW portfolio spreads. The minimum of correlations between EW spreads is -0.35 and it is between return-on-assets and O-score anomalies. For the VW spread correlations (Figure 2), the strongest relation is again between GP and ROA with a correlation of 0.45. However, for VW spreads the lowest correlation (-0.25) is between AG and ROA.

Table 3 presents the time-series averages of cross-sectional median characteristics of anomaly portfolios. We can observe that the high momentum quintile portfolio has higher market capitalization, lower market exposure, lower B/M, and is less illiquid than the low momentum portfolio, on average. For asset growth, although the characteristics of B/M and market beta are alike, the low asset growth portfolio is smaller and more illiquid than the high asset growth quintile on average. Both for GP and ROA, the high profitability portfolio is bigger and has a higher average valuation. This finding indicates the low correlation of GP and ROA with HML factor. For the investment anomaly, the only meaningful difference in terms of characteristics is that

low investment firms are also the smaller ones in terms of their market capitalizations. Accruals anomaly quintile portfolios do not have substantial differences across stock characteristics. Per composite equity issues, the firms with high stock issuance are the ones with high beta and high liquidity on average.

Figure 1

Correlations between EW single-sorted portfolio spreads and FF3 factors.

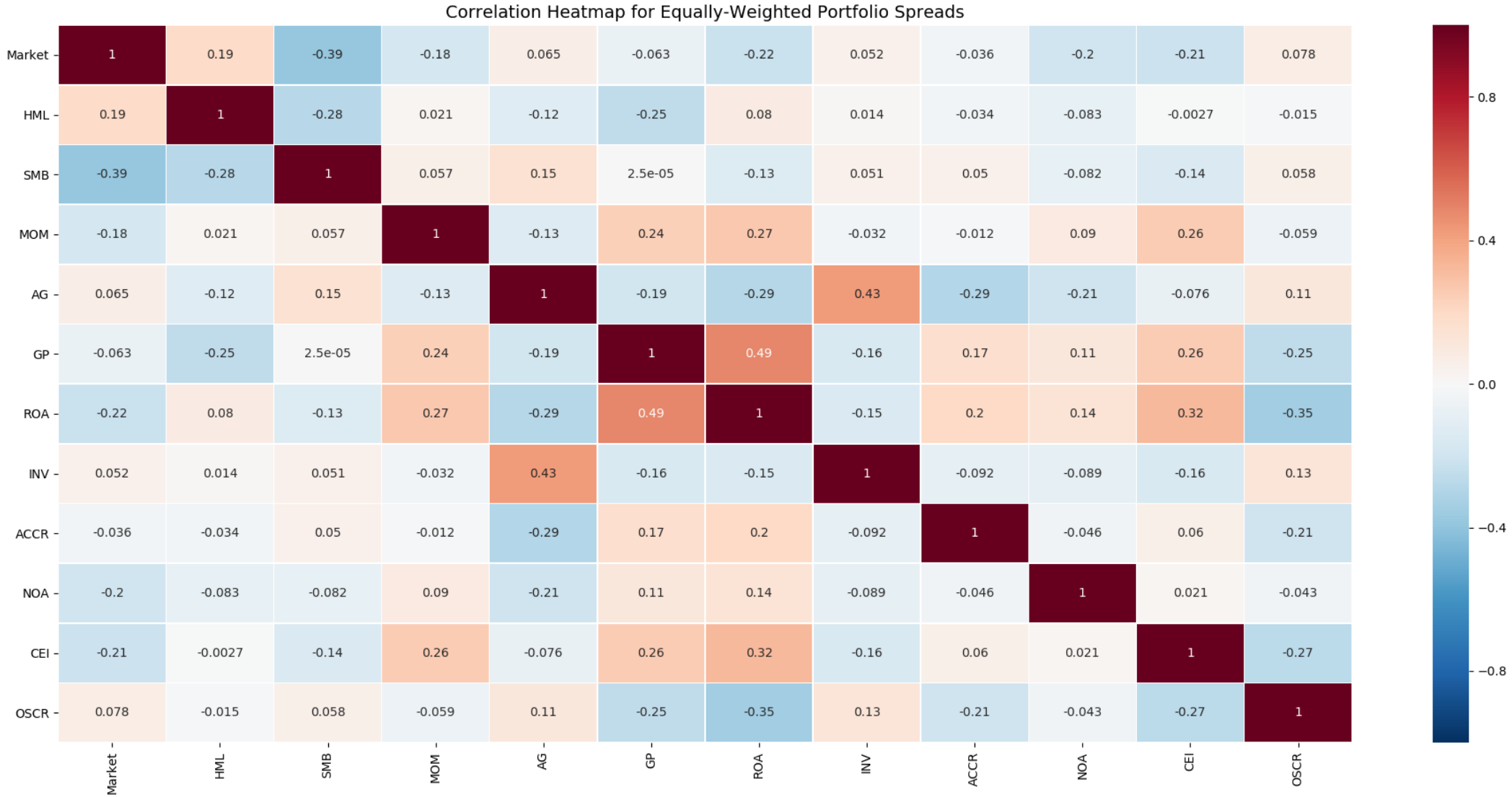

Figure 2

Correlations between VW single-sorted portfolio spreads and FF3 factors.

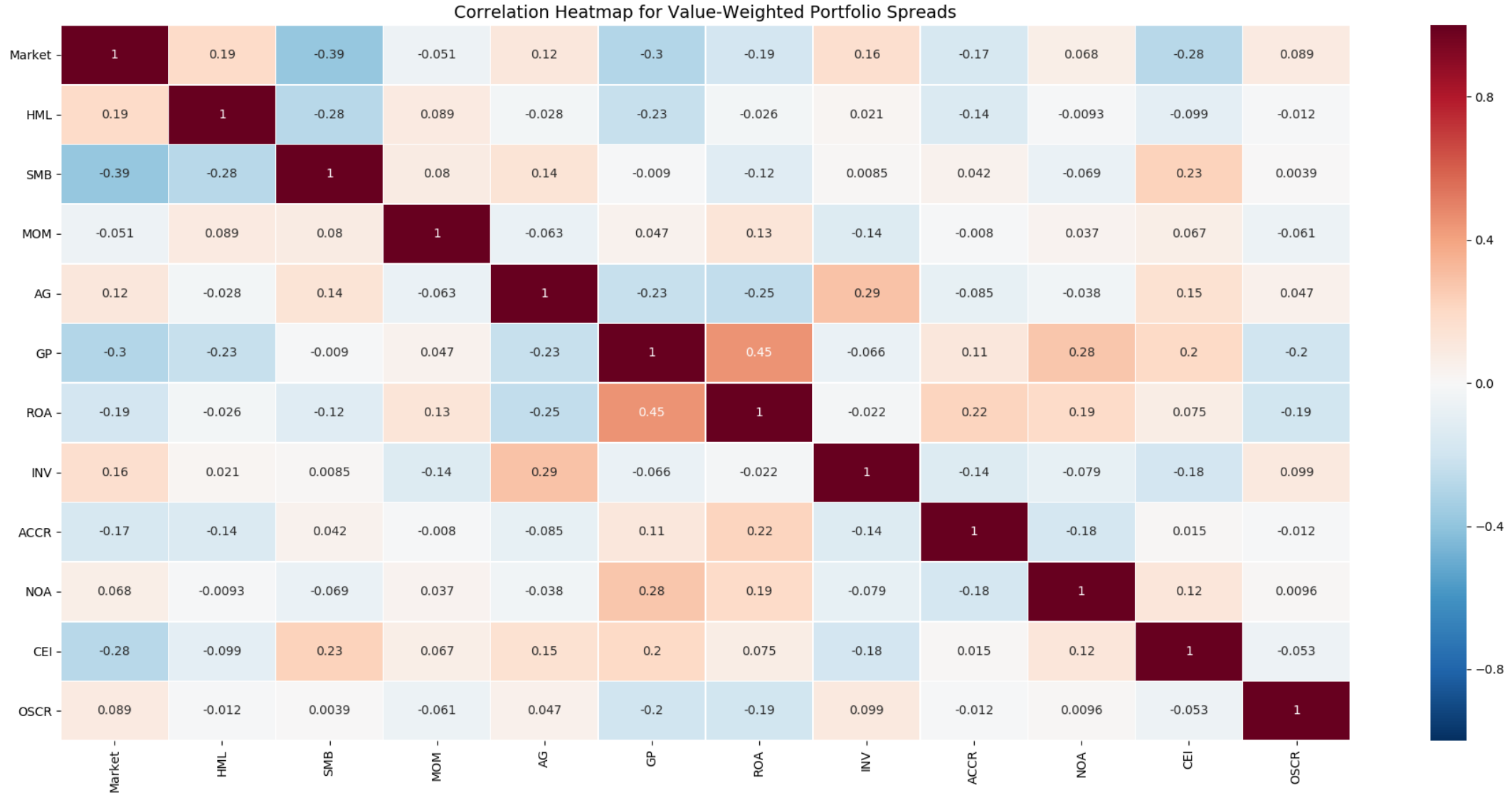

Table 3

Characteristics of anomaly portfolios. The table reports summary characteristics of the quintile portfolios. Characteristics are computed as time-series averages of median values at the end of month t (portfolio formation). Size is market capitalization (in million Turkish Lira), B/M is book-to-market ratio, Beta is market beta, computed from the market model, Illiq is the Amihud (2002) illiquidity measure.

Momentum				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
High Momentum	263,005.03	0.88	0.64	3.29
2	271,496.50	0.90	0.79	4.71
3	197,651.37	0.90	0.86	5.13
4	150,849.92	0.91	0.89	5.96
Low Momentum	119,067.10	0.90	0.87	4.54
Asset Growth				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low AG	108,903.73	0.86	0.74	6.12
2	148,723.84	0.89	0.91	4.91
3	211,442.97	0.90	0.86	4.80
4	241,822.94	0.88	0.81	4.26
High AG	162,893.21	0.87	0.74	4.14
Gross Profitability				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
High GP	235,266.01	0.86	0.53	6.38
2	194,948.24	0.86	0.75	5.36
3	189,127.17	0.89	0.87	5.30
4	157,698.62	0.89	1.00	3.69
Low GP	86,101.12	0.90	1.05	3.82
Return-on-Asset				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
High ROA	291,916.50	0.84	0.64	5.08
2	263,102.62	0.89	0.81	4.89
3	190,023.40	0.90	0.92	3.83
4	129,069.47	0.89	0.97	4.71
Low ROA	80,423.24	0.89	0.74	5.57

Investment				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low INV	132,028.07	0.89	0.78	4.64
2	132,448.88	0.89	0.88	5.07
3	210,863.32	0.90	0.81	4.33
4	255,330.20	0.89	0.80	4.87
High INV	207,690.01	0.87	0.73	4.74

Accruals				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low ACCR	157,754.49	0.86	0.76	3.93
2	252,541.23	0.90	0.83	3.18
3	242,503.68	0.90	0.88	3.34
4	204,165.15	0.91	0.90	3.87
High ACCR	145,352.01	0.88	0.76	3.83

Net Operating Assets				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low NOA	161,452.01	0.91	0.78	3.52
2	194,732.12	0.91	0.72	4.33
3	126,317.11	0.87	0.82	5.77
4	155,003.37	0.84	0.89	5.94
High NOA	170,189.43	0.86	0.88	4.37

Composite Equity Issues				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low CEI	352,578.40	0.85	0.77	5.59
2	535,434.12	0.91	0.81	3.23
3	98,421.50	0.89	0.80	5.20
4	87,113.69	0.91	0.90	5.49
High CEI	130,478.37	0.96	0.80	3.72

O-Score				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
Low OSCR	65,823.13	0.89	0.70	5.51
2	199,607.25	0.88	0.87	5.23
3	310,602.60	0.86	0.85	4.38
4	278,386.86	0.90	0.78	4.16
High OSCR	134,491.88	0.88	0.79	5.37

3.2 Double Independent Portfolio Sorts

The mixed results between single sort EW and VW portfolios are suggestive of different behaviors of the anomalies across different level of firm sizes. To investigate further, each month t, we sort stocks independently into portfolios according to size and the corresponding anomaly proxy variable. Because of the limited number of stocks in our sample, we sort stocks into terciles for both size and each proxy variable. To calculate the anomaly factor return we average the bivariate-sorted portfolio returns across the terciles of the size portfolios. Table 4 reports the average spread of extreme portfolio returns after controlling for size.

Table 4

Double independent sorts. Entries in the table are average returns of value-weighted double-sorted portfolios, averaged along the *Size*. At the end of each month, stocks are sorted independently into 9 portfolios (3 x 3 sort), according to *Size* and each of the anomaly proxy. T-statistics, based on Newey-West adjusted standard errors, are reported in brackets.

Double Independent Portfolio Sorts		
Anomaly	**Mean Spread (%)**	**FF3 alpha (%)**
MOM	0.54	0.54
	(1.86)	(1.77)
AG	-0.48	-0.44
	(-2.32)	(-2.12)
GP	0.42	0.63
	(2.04)	(3.04)
ROA	0.86	0.94
	(3.71)	(3.98)
INV	0.07	0.14
	(0.30)	(0.61)
ACCR	-0.23	-0.29
	(-1.02)	(-1.21)
NOA	-0.12	0.01
	(-0.64)	(0.04)
CEI	0.50	0.60
	(2.44)	(2.91)
OSCR	0.05	-0.08
	(0.18)	(-0.29)

When we control for size, average sample spread for momentum became significant at 10% level with a mean spread of 0.54% and T-stat of 1.86. The asset growth anomaly still generates negative expected returns (-0.48%) with a T-stat of -2.32. Gross profitability and return-on-assets spreads are both positive (0.42% and 0.85%, respectively) and significant, as in the single sort case (T-stats are 2.04 and 3.71, respectively). Composite equity issues anomaly is also significant with a T-stat of 2.44 and monthly mean spread of 50 basis points. Total accruals anomaly became insignificant with a T-stat of -1.02 compared to being slightly significant in the single portfolio sort scenario. However, its negative sign is consistent with the single sorting results with a mean spread of -0.23%.

Investment, net operating asset, and O-score anomalies are insignificant in the double sort case.

3.3 Fama-MacBeth Regression Analysis

We perform Fama-MacBeth regression analysis, whereby at time t we regress stock returns on lagged values of each anomaly proxy variable along with beta, size, and B/M. As an extension, we also carry on Fama-MacBeth analysis by including the illiquidity factor – Illiq. Each month t, regressions are performed, and time series averages of the cross-sectional regression coefficients are presented in Table 1 in the appendix for brevity.

The Fama-MacBeth analysis results for individual anomalies are generally in line with those of the portfolio analysis. Asset growth, gross profitability, return-on-asset, and composite equity issues anomalies proxy variables have significant predictive power for expected returns and are robust to controlling for other characteristic

variables, namely beta, B/M, size, and Illiq. Momentum is not significant with a T-stat of 1.57 but has a positive sign. Investment, accruals, net operating assets, and O-score are not significant.

Turning to the controlling for illiquidity specification, we see momentum gets weaker when controlled for illiquidity with a T-stat of 1.52 and a positive time-series average coefficient. Like momentum, the investment anomaly also weakens after controlling for illiquidity (T-stat decreases from 1.62 to 1.35). The significant anomalies, asset growth, gross profitability, return-on-assets, and composite equity issues remain significant after controlling for illiquidity. Total accruals, net-operating-assets, and o-score anomalies' coefficients remain insignificant.

Turning to the control variables, we observe that B/M is significant for all individual anomaly regression settings even controlled for illiquidity. Illiq also turned out to be significant with a sole exception, return-on-asset anomaly. When Illiq is insignificant, size becomes significant for the first time.

We also control for all anomalies simultaneously in a regression framework with and without the illiquidity factor. In the full regression setting, the most robust coefficients belong to B/M, asset growth, gross profitability, and composite equity issues. After controlling for illiquidity in the full regression specification, B/M, asset growth, gross profitability, and composite equity issues remain significant. Momentum's coefficient, on the other hand, becomes insignificant and negative.

CHAPTER IV

COMPOSITE MISPRICING MEASURE

After analyzing individual anomalies, we embarked to composite mispricing measure calculations. As discussed earlier, we calculated the mispricing ranking of a stock by averaging all the rankings according to individual anomalies. We use momentum, asset growth, gross profitability, return-on-asset, accruals, and composite equity issues anomalies to calculate COMP. Table 5 presents below portfolio analysis results.

The EW and VW portfolio spreads are significant. Moreover, none of the individual anomalies have this level of significance for EW and VW portfolios as well as FF3 alphas at the same time. Moreover, COMP keeps its significance when controlled for size by double sorting the portfolios.

When we control for beta, B/M, size, and illiquidity in Fama-MacBeth regression setting, COMP measure turned to be highly significant effect on expected returns with a T-stat of 7.01 (Results shown in the appendix for brevity).

For control variables, the quintile portfolios have higher market capitalization, less exposed to market, high valuation as their composite measure increases. Moreover, those characteristics increase monotonically from overpriced portfolio to underpriced portfolio. There is not a meaningful pattern for illiquidity measure of the quintiles.

Table 5

Portfolio analysis of Composite Mispricing Measure. Entries in the Panel A are average value- and equally-weighted returns of portfolios sorted on the basis of COMP. At the end of each month t, stocks are sorted into decile portfolios according to COMP within month t. Portfolios are held for 1-month. The FF3 alphas are based on a three-factor model in which portfolio returns are regressed on Market, value, and size. The spread portfolios are formed by a long position in the most underpriced portfolio and a short position in most the overpriced portfolio. Entries in the Panel B are average returns of value-weighted double-sorted portfolios, averaged along the *Size*. At the end of each month, stocks are sorted independently into 9 portfolios (3 x 3 sort), according to *Size* and each of the anomaly proxy. T-statistics, based on Newey-West adjusted standard errors, are reported in brackets.

Panel A: Univariate Sort Portfolio Results

Composite Mispricing Measure				
	Equally-Weighted		Value-Weighted	
Quintile	Average Excess Return (%)	FF3 Alpha (%)	Average Excess Return (%)	FF3 Alpha (%)
High COMP	1.26	0.70	0.81	0.41
2	0.95	0.36	0.28	-0.34
3	0.60	-0.10	0.73	0.15
4	0.39	-0.29	0.37	-0.24
Low COMP	0.02	-0.59	-0.49	-1.01
High COMP - Low COMP	1.25	1.28	1.31	1.42
	(4.12)	(4.34)	(3.03)	(3.48)

Panel B: Bivariate Sort Portfolio Results

COMP	
Mean Spread (%)	FF3 alpha (%)
1.21	1.26
(4.93)	(5.11)

To see the relation between composite mispricing measure, we present its EW and VW spreads' correlations with individual anomalies' spreads. (Table XX). The highest correlations with composite measure belong to profitability anomalies, gross profitability, and return-on-asset anomaly. The composite measure has very low

correlations with two of FF3 factors, value and size. Moreover, COMP is negatively correlated with the market.

Table 6

Characteristics of COMP portfolios. The table reports summary characteristics of the quintile portfolios formed based on COMP measure. Characteristics are computed as time-series averages of median values at the end of month t (portfolio formation). Size is market capitalization (in million Turkish Lira), B/M is book-to-market ratio, Beta is market beta, computed from the market model, Illiq is the Amihud (2002) illiquidity measure.

Composite Mispricing Measure				
Quintile	**Size**	**Beta**	**B/M**	**Illiq**
High COMP	374,492.42	0.84	0.63	5.08
2	249,446.06	0.87	0.76	4.89
3	168,105.08	0.89	0.88	4.75
4	113,706.02	0.89	0.92	4.81
Low COMP	70,074.24	0.91	0.95	5.04

Next, we propose a pricing model for BIST:

$$r_i = \alpha_i + \beta_{Market} \cdot (R_{Market} - Rf) + \beta_{HML} \cdot HML + \beta_{SMB} \cdot SMB + \beta_{COMP} \cdot COMP + \epsilon_i,$$

where r_i is the individual stock's excess return and COMP is the composite mispricing factor calculated in the same manner as HML and SMB. After imposing our model, we checked several statistics for FF3 and our model abilities to capture the anomaly EW and VW long-short spreads. Table 7 presents average absolute alpha, average absolute t-statistic of alpha, the number of anomalies for which the model produces the lowest absolute alpha among the four models being compared, and the Gibbons, Ross, and Shanken (1989) "GRS" test of whether all alphas equal zero. As it is clear from the table, our proposed model generates lowest average absolute alpha, averagethe absolute

t-statistic, and F-statistic of GRS test. That is, our model captures better the systematic drivers of returns in BIST.

Table 7

Summary measures of models' abilities to explain anomalies. The table reports measures that summarize the degree to which anomalies produce alpha under the three-factor model of Fama and French (1993; and the four-factor mispricing-factor model introduced in this study. Also reported are measures based on the average unadjusted return spreads (the alphas in a model with no factors). For each model, the table reports the average absolute alpha, average absolute t-statistic, the F-statistic and associated p-value for the "GRS" test of Gibbons, Ross, and Shanken (1989), and the number of anomalies for which the model produces the smallest absolute alpha among the models being compared in the table.

Panel A: Composite Measure Anomalies

	Equally-Weighted			Value-Weighted		
Measure	**Unadjusted**	**FF3**	**Mispricing Model**	**Unadjusted**	**FF3**	**Mispricing Model**
Average |α|	0.74	0.78	0.48	0.70	0.79	0.60
Average |*t*|	2.83	2.96	1.90	1.62	1.86	1.26
GRS	5.30	6.26	4.64	2.08	2.73	1.94
pGRS	0.000066	0.000009	0.000271	0.059832	0.015934	0.079439
Number of min |α|	-	0	6	-	1	5

Panel B: All Anomalies

	Equally-Weighted			Value-Weighted		
Measure	**Unadjusted**	**FF3**	**Mispricing Model**	**Unadjusted**	**FF3**	**Mispricing Model**
Average |α|	0.55	0.58	0.35	0.58	0.64	0.53
Average |*t*|	2.12	2.19	1.36	1.33	1.47	1.07
GRS	3.50	4.12	3.11	1.50	1.96	1.51
pGRS	0.000719	0.000123	0.002127	0.154474	0.049566	0.150717
Number of min |α|	-	0	9	-	3	6

CHAPTER V

ROBUSTNESS

In this section, we implemented two robustness checks: the behavior of anomalies during non-crisis subperiods and when penny stocks are included in the analysis.

We split our sample period into two subperiods excluding the period from July 2008 to the end of 2009. Particularly, the first subperiod is from January 2003 to June 2008, and the second subperiod is from January 2010 to December 2016. Table 8 below presents subperiod mean spreads of EW and VW portfolios and their respective t-statistics. The significant anomalies asset growth (t-stats are -2.17 and -3.36 for subperiod respectively), gross profitability (t-stats are 2.56 and 2.77 for subperiods respectively), return-on-asset (t-stats are 3.04 and 2.24 for subperiods respectively), and composite equity issues (t-stats are 3.05 and 3.37 for subperiods respectively) EW mean spreads are also significant for both periods. Their VW spreads are also significant for the first subperiod except for composite equity issues (t-stats are -2.47 for AG, 1.99 for GP, 2.21 for ROA). However, for the second subperiod, the only VW significant spread belongs to composite equity issues (mean 1.13%, t-stat 2.51). EW momentum spreads is significant at 10% level for both subperiods. Nevertheless, VW momentum spreads for subperiods are neither significant nor consistent in terms of their signs.

Composite measure is significant across all subperiods and portfolio weighting schemes which reveals composite measure's robustness.

Table 8

Statistics of portfolio spreads for subperiods. The table presents EW and VW average spread and T-statistics for periods for two subperiods: January 2003 to June 2008 and January 2010 to December 2006. All T-statistics are based on Newey-West adjusted standard errors.

	EW				VW			
Anomalies	**2003-2008.06**		**2010-2016**		**2003-2008.06**		**2010-2016**	
	Mean (%)	**T-stat**	**Mean (%)**	**T-stat**	**Mean (%)**	**T-stat**	**Mean (%)**	**T-stat**
MOM	0.95	1.67	0.66	1.72	0.84	1.07	-0.45	-0.64
AG	-0.88	-2.17	-1.01	-3.36	-1.65	-2.47	-0.67	-1.56
GP	1.02	2.56	0.90	2.77	1.13	1.99	0.14	0.32
ROA	1.33	3.04	0.82	2.24	1.34	2.21	0.64	1.06
INV	-0.65	-1.69	-0.41	-1.25	0.08	0.14	-0.25	-0.56
ACCR	-0.46	-0.82	-0.48	-1.47	-2.47	-2.47	0.24	0.54
NOA	-1.18	-3.32	0.35	1.31	-0.12	-0.18	0.55	1.30
CEI	1.27	3.05	1.02	3.37	0.30	0.49	1.13	2.51
OSCR	-0.43	-1.11	-0.26	-0.92	-1.49	-1.93	1.03	1.07
COMP	1.67	3.00	1.43	4.09	2.44	3.57	1.20	2.26

Next, we checked if any of the anomalies' findings would be affected when we include the penny stocks. Thus, we repeat our tests by removing market capitalization filter. That is, we include firms with market capitalization less than the tenth percentile of all stocks' market capitalizations each month. When we include penny stocks, asset growth, gross profitability, return-on-asset are still significant for EW and VW spreads. Momentum is significant for EW spread but insignificant and has negative mean for VW spread.

Composite measure is still significant and has positive means for EW and VW spreads (mean spreads are 1.34% and 1.38%, t-stats are 4.52 and 3.12 for EW and VW portfolios respectively.)

Table 9

Univariate portfolio analysis when market capitalization filter is lifted. The table presents EW and VW portfolio mean spreads. T-statistics, based on Newey-West adjusted standard errors, are reported in brackets.

	EW Portfolios Mean Spread (%) and T-stat	VW Portfolio Mean Spread (%) and T-stat
MOM	0.56 (1.72)	-0.28 (-0.50)
AG	-0.72 (-3.21)	-0.93 (-2.57)
GP	0.91 (3.96)	0.63 (1.76)
ROA	0.91 (3.45)	0.85 (2.06)
INV	-0.29 (-1.25)	0.34 (0.87)
ACCR	-0.20 (-1.13)	-0.52 (-1.82)
NOA	-0.31 (-1.36)	0.36 (0.87)
CEI	1.07 (4.65)	0.44 (1.24)
OSCR	-0.41 (-1.75)	0.17 (0.26)
COMP	1.34 (4.52)	1.38 (3.12)

CHAPTER VI

CONCLUSION

We examined 9 prominent anomalies for BIST. Our study revealed that gross profitability, return-on-assets, asset growth, and composite equity issues are the most robust anomalies for BIST. Moreover, asset growth and accruals anomalies work in the opposite direction than US-based studies point out. EW portfolio analysis shows that Momentum is significant at 10% level. However, momentum manifests itself more like a reversal for VW portfolio spreads.

Next, we construct a composite mispricing measure by using the momentum, asset growth, gross profitability, return-on-assets, accruals, and composite equity issues. This measure turned out to be more consistent in terms of being anomalous. Moreover, we propose a four-factor asset pricing model incorporating mispricing measure with the market, value, and size factors and compared it to Fama French 3-factor model in terms of several statistics. Our comparison based on these measures assert that our model is superior to Fama French 3-factor model on explaining anomalies.

APPENDIX

Figure 3

Average portfolio sizes. Figure shows the evolution of the minimum number of stocks and average number of stocks per quintile across anomalies over the sample period.

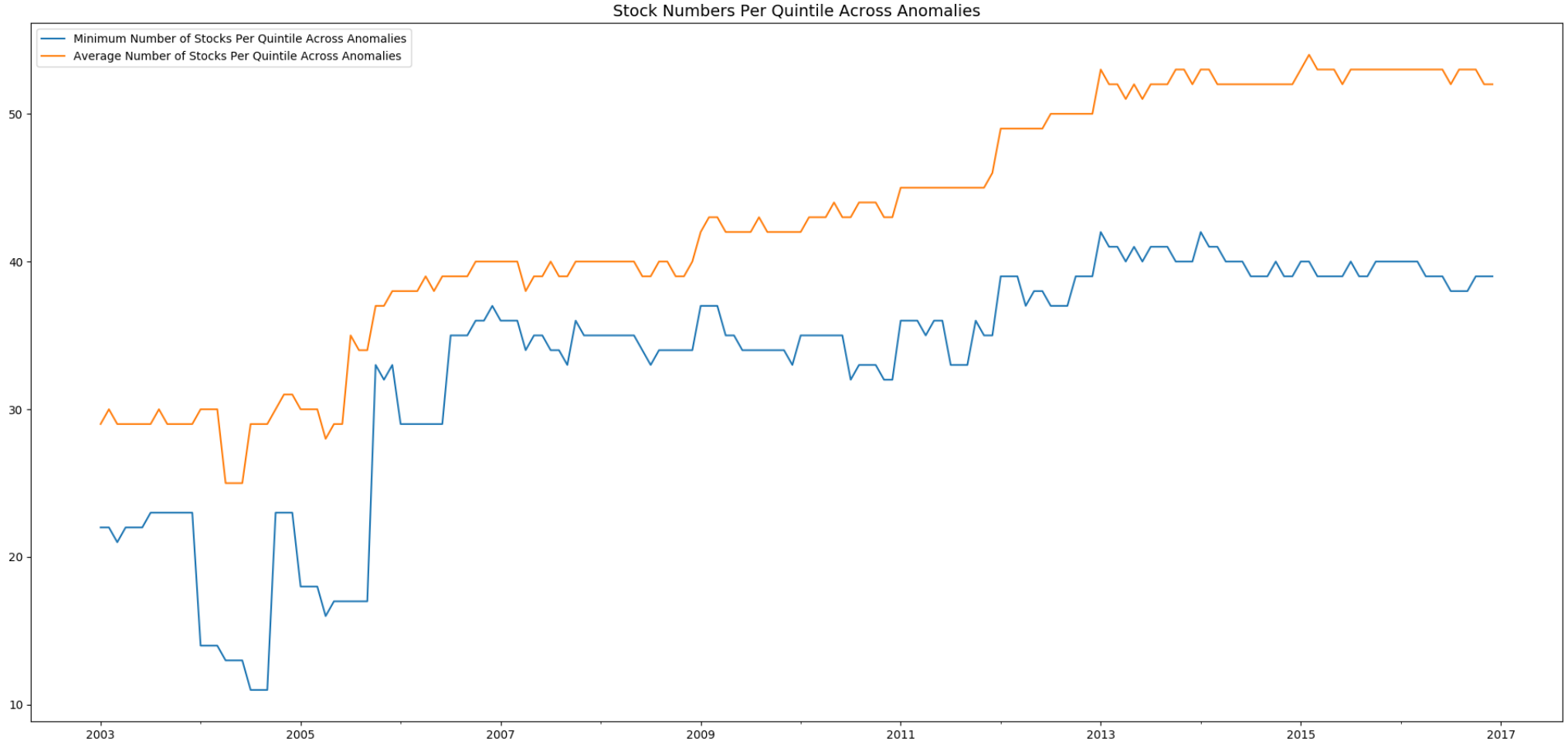

Table 10

Fama-MacBeth regression results. The table reports results from Fama-MacBeth regressions. Each month, stock returns are regressed on lagged values of individual anomaly proxies, controlling for beta, B/M, *Size*, and *Illiq*. Entries in the table are the time-series averages of the cross-sectional regressions' estimated slope coefficients. B/M, *Size*, and *Illiq* the logarithms of the respective predictor variables. T-statistics are calculated based on Newey-West corrected standard errors.

MOM		
	coef	**t-stat**
beta	-0.002	-0.505
B/M	0.004	3.288
size	0.000	-0.459
MOM	0.007	1.571
	coef	**t-stat**
beta	0.001	0.144
B/M	0.004	3.394
illiq	0.002	3.042
size	0.001	0.799
MOM	0.007	1.515

AG		
	coef	**t-stat**
beta	-0.001	-0.192
B/M	0.003	2.617
size	-0.001	-0.796
AG	0.020	3.553
	coef	**t-stat**
beta	0.002	0.609
B/M	0.003	2.634
illiq	0.002	3.477
size	0.001	0.616
AG	0.022	3.614

GP		
	coef	**t-stat**
beta	-0.001	-0.247
B/M	0.005	3.906
size	-0.001	-0.800
GP	0.109	5.551
	coef	**t-stat**
beta	0.002	0.448
B/M	0.005	3.870
illiq	0.002	2.913
size	0.000	0.373
GP	0.103	5.187

ROA		
	coef	**t-stat**
beta	-0.002	-0.394
B/M	0.004	3.258
size	-0.001	-0.631
ROA	0.131	3.602
	coef	**t-stat**
beta	-0.001	-0.156
B/M	0.004	2.729
illiq	-0.001	-1.325
size	0.141	4.139
ROA	0.140	4.060

INV		
	coef	**t-stat**
beta	0.001	0.180
B/M	0.004	2.818
size	0.000	-0.521
INV	0.012	1.623
	coef	**t-stat**
beta	0.004	1.005
B/M	0.004	2.764
illiq	0.003	3.471
size	0.001	0.994
INV	0.011	1.349

ACCR		
	coef	**t-stat**
beta	-0.002	-0.527
B/M	0.003	2.094
size	-0.001	-0.528
ACCR	0.000	0.033
	coef	**t-stat**
beta	0.000	0.088
B/M	0.003	2.206
illiq	0.002	3.048
size	0.001	0.858
ACCR	0.003	0.210

NOA		
	coef	**t-stat**
beta	-0.001	-0.379
B/M	0.003	2.683
size	0.000	-0.403
NOA	0.001	0.244
	coef	**t-stat**
beta	0.001	0.309
B/M	0.003	2.712
illiq	0.002	3.184
size	0.001	0.895
NOA	-0.001	-0.243

CEI		
	coef	**t-stat**
beta	0.001	0.268
B/M	0.004	3.015
size	0.000	-0.255
CEI	-0.022	-3.950
	coef	**t-stat**
beta	0.003	0.783
B/M	0.004	3.039
illiq	0.001	2.411
size	0.001	0.685
CEI	-0.024	-4.341

OSCR		
	coef	**t-stat**
beta	-0.002	-0.441
B/M	0.003	2.299
size	0.000	-0.498
OSCR	0.000	0.218
	coef	**t-stat**
beta	0.001	0.233
B/M	0.003	2.377
illiq	0.002	3.254
size	0.001	0.865
OSCR	0.000	0.049

All except illiq		
	coef	**t-stat**
beta	-0.004	-0.969
B/M	0.005	2.908
size	-0.001	-1.025
MOM	-0.002	-0.438
AG	0.037	3.745
GP	0.065	2.396
ROA	0.078	1.534
INV	-0.007	-0.586
ACCR	0.020	1.270
NOA	-0.001	-0.196
CEI	-0.031	-3.670
OSCR	0.000	-0.258

All with illiq		
	coef	**t-stat**
beta	-0.003	-0.660
B/M	0.005	3.024
illiq	0.002	1.703
size	0.000	0.007
MOM	-0.003	-0.523
AG	0.038	3.764
GP	0.063	2.346
ROA	0.083	1.577
INV	-0.005	-0.439
ACCR	0.022	1.370
NOA	-0.001	-0.253
CEI	-0.038	-4.158
OSCR	0.000	-0.366

Table 11

The correlations between COMP and portfolio. Table reports correlations between individual anomaly EW and VW portfolio spreads' correlations with EW and VW COMP spreads.

EW Portfolio Spreads		**Market**	**HML**	**SMB**	**MOM**	**AG**	**GP**	**ROA**	**INV**	**ACCR**	**NOA**	**CEI**	**OSCR**
	COMP	-0.29	0.01	-0.14	0.56	-0.42	0.62	0.75	-0.22	0.00	0.19	0.53	-0.31
VW Portfolio Spreads		**Market**	**HML**	**SMB**	**MOM**	**AG**	**GP**	**ROA**	**INV**	**ACCR**	**NOA**	**CEI**	**OSCR**
	COMP	-0.39	-0.03	-0.06	0.38	-0.38	0.49	0.58	-0.24	0.06	0.10	0.25	-0.16

BIBLIOGRAPHY

[1] Alkan, U., Guner, B., 2018. Preferences for lottery stocks at Borsa Istanbul. Journal of International Financial Markets, Institutions, and Money 55, 211-223.

[2] Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

[3] Atilgan, Y., Demirtas, O., Gunaydin, D., 2016. Liquidity and equity returns in Borsa Istanbul. Applied Economics 48 (52), 5075–5092.

[4] Atilgan, Y., Demirtas, O., Gunaydin, D., 2016. Share issuance and equity returns in Borsa Istanbul, International Review of Economics and Finance, 43, 320-333.

[5] Barillas, Francisco, and Jay Shanken, 2015a, Comparing asset pricing models, Journal of Finance 73,715-754.

[6] Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, Journal of Finance 63, 2899–2939.

[7] Carhart, Mark M., 1997, On persistence in mutual fund performance, Journal of Finance 52, 57–82.

[8] Cochrane, John H., 2011, Presidential Address: Discount Rates, Journal of Finance, 66, 1047-1108.

[9] Daniel, Kent D., and Sheridan Titman, 2006, Market reactions to tangible and intangible information, Journal of Finance 61, 1605–1643.

[10] Fama, Eugene F., and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3–56.

[11] Fama, Eugene F., and Kenneth French, 2006, Profitability, investment, and average returns, Journal of Financial Economics 82, 491–518.

[12] Fama, Eugene F., and Kenneth French, 2008, Dissecting anomalies, Journal of Finance 63, 1653–1678.

[13] Fama, Eugene F., and Kenneth French, 2015, A five-factor asset pricing model, Journal of Financial Economics 16, 1–22.

[14] Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, "… and the cross-section of expected returns," The Review of Financial Studies 29, 5-68.

[15] Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets? Journal of Accounting and Economics 38, 297–331.

[16] Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, Review of Financial Studies 28, 650–705.

[17] Hou, Kewei, Chen Xue, and Lu Zhang, 2017, Replicating Anomalies,

Working paper, Ohio State University, University of Cincinnati, and Ohio State University.

[18] Stambaugh, R., Jianfeng, Y., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70 (5), 1903–1948.

[19] Stambaugh, R., Jianfeng, Y., Yuan, Y., 2016. Mispricing Factors.Review of Financial Studies 30 (4), 1270–1315.

[20] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for market efficiency, Journal of Finance 48, 65–91.

[21] Ince, Ozgur S., and Burt R. Porter, 2006, Individual equity return data from Thomson Datastream: Handle with care!, Journal of Financial Research 29, 463–479.

[22] McLean, R. David, and Jeffrey Pontiff, 2015, Does academic research destroy stock return predictability?, Journal of Finance 71, 5-32.

[23] Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, Journal of Financial Economics 108, 1–28.

[24] Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, Journal of Accounting Research 18, 109–131.

[25] Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71, 289–315.

[26] Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, Journal of Finance 70, 1903–1948.

[27] Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, Journal of Financial and Quantitative Analysis 39, 677–700.