YAŞAR UNIVERSITY

GRADUATE SCHOOL

PHD THESIS

ESSAYS ON INTERNATIONAL PORTFOLIO INVESTMENTS

PELİN BENGİTÖZ

THESIS ADVISOR: ASSOC. PROF. (PHD) MEHMET UMUTLU

PHD PROGRAM IN FINANCE

PRESENTATION DATE: 02.04.2021

BORNOVA / İZMİR
APRIL 2021

We certify that, as the jury, we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of the Doctor of Philosophy.

Jury Members:	**Signature:**
Assoc.(PhD) Mehmet UMUTLU Yaşar University	....
Assoc.(PhD) Ebru SAYGILI Yaşar University	....
Assist.(PhD) Hakan ÖZKAYA Dokuz Eylül University	....
Assoc.(PhD) Adam ZAREMBA Montpellier Business School	....
Assoc.(PhD) Mehmet Oğuz KARAHAN Yaşar University	....

Prof. (PhD) Mustafa Arslan Örnek

Director of the Graduate School

ABSTRACT

ESSAYS ON INTERNATIONAL PORTFOLIO INVESTMENTS

Bengitöz, Pelin
PHD, Finance
Advisor: Assoc. Prof. (PhD) Mehmet UMUTLU
April 2021

The first and second chapters of the dissertation mainly focus on several return predictors, which are measures of volatility, skewness, momentum, and profitability; size and value effects; and other measures, such as investments and net share issuance. In addition, the cross-sectional relation between the return range, a newly proposed proxy of total volatility, and future index returns are examined for the first time in the literature. In the first dissertation chapter, the significance of the effects of these nineteen anomalies are examined at the international index level using 19 industries specified for 37 countries from January 1973 to July 2015. The results of both the portfolio-level analyses and index-level cross-sectional regressions indicate that all volatility measures, including the return range, exclusively affect returns on small-cap indexes. Additionally, maximum and minimum return anomalies also persistently exist across all size quintiles. The skewness measures significantly affect small-cap indexes while the momentum effect is significant in both small- and medium-cap indexes. Depending on their definitions, profitability measures significantly affect both small- and large-cap portfolios whereas the value effect has significant explanatory power on indexes from all size segments. Lastly, the return range can be used as a very practical measure of total volatility instead of the standard deviation.

The second chapter investigates the effects of these nineteen index attributes on index returns for six different regions: North America, Europe, Asia-Pacific, South America, MENA, and Japan. This chapter considers the different characteristics of these regions that determine the degree of market segmentation or integration across regions, and

therefore performs the regional versions of the asset-pricing models. The results suggest, first, that all volatility measures and the return range significantly predict index returns from Europe, Asia-Pacific, South America, and Japan. Second, the maximum and minimum return anomalies significantly predict index returns regardless of region. Third, there are significant size and value effects for all regions except for Japan, which only shows size effect. Fourth, there are significant momentum effects in North America, Europe, and MENA while the profitability effect has a significant explanatory power for Europe and Asia-Pacific, depending on its definition. Fifth, the skewness measures only significantly affect the returns for European country-industry indexes. Lastly, the Fama-MacBeth regressions provide almost identical results to the portfolio analyses.

The third chapter examines the value effect based on earnings-to-price ratio (*EP*) by decomposing *EP* into four independent components, which are lagged *EP* value, change in earnings, momentum, and reversal, following the decomposition methodology of Fama and French (2008). In addition to the sample from the second chapter, this chapter includes a sample of country indexes with 51 local country indexes. The results show a significant *EP* ratio effect while the components of *EP* also include independent information that can be used to enhance estimates of future returns for both country-industry and country indexes in most of the cases. Additionally, decomposition of *EP* matters for all regions of country-industry indexes except South America. However, the results depend on the time horizons used for the lagged value of *EP*. Lastly, the decomposition analyses for the size-based portfolios of both samples show that the components of *EP* reveal more information about small-cap indexes.

Keywords: portfolio management, international investors, asset-pricing, Fama-MacBeth regressions, volatility measures, index returns, return predictability, value effect, decomposition.

ÖZ

ULUSLARARASI PORTFÖY YATIRIMLARI ÜZERİNE MAKALELER

Bengitöz, Pelin
Doktora Tezi, Finans
Danışman: Doç. Dr. Mehmet UMUTLU
Nisan 2021

Bu tez çalışmasının birinci ve ikinci bölümü ağırlıklı olarak volatilite, çarpıklık, momentum, karlılık, özerk ölçütler, büyüklük ve değer etkileri, yatırım ve net hisse senedi ihracı değerleri olmak üzere birçok getiri tahminleyicisini ele almaktadır. Ek olarak, toplam volatilite ölçütü olarak kullanılması önerilen getiri aralığı değişkeni ile beklenen getiri oranları arasındaki kesitsel ilişki literatürde ilk defa bu bölümde incelenmiştir. Birinci bölümde, 19 adet anomalinin getiri oranları üzerindeki etkisinin anlamlılığı uluslararası endeks seviyesinde araştırılmıştır. Bu kapsamda, Ocak 1973 ve Temmuz 2015 tarihleri arasında 37 ülke için tanımlanmış olan 19 adet endüstrinin yer aldığı yerel endüstri endeksleri kullanılmıştır. Hem portföy bazlı hem de endeks bazlı kesitsel regresyon analizlerinin sonuçları, getiri aralığı değişkeni başta olmak üzere tüm volatilite ölçütlerinin özellikle düşük piyasa değerli endeks getirilerini etkilediğini göstermektedir. Ayrıca, maksimum ve minimum getiri anomalilerinin ise piyasa değeri fark etmeksizin her portföy için anlamlı olduğu sonucuna varılmıştır. Buna ek olarak, çarpıklık ölçütleri düşük piyasa değerli endeks getirilerini anlamlı bir şekilde etkilerken, momentum etkisi hem düşük hem de orta piyasa değerli endeksler üzerinde anlamlıdır. Tanımlarına bağlı olarak, karlılık etkisi düşük ve yüksek piyasa değerli portföylerde anlamlı iken değer etkisi ise her seviye piyasa değerli endeks getirileri üzerinde anlamlı bir açıklayıcı güce sahiptir. Son olarak, geleneksel ölçüt olan standart sapma yerine, getiri aralığının daha pratik bir toplam volatilite ölçütü olarak kullanılabileceği tespit edilmiştir.

İkinci bölümde, 19 adet anomalinin endeks getiri oranları üzerindeki etkisi Kuzey Amerika, Avrupa, Asya-Pasifik, Güney Amerika, ODKA (Orta Doğu ve Kuzey Afrika)

ve Japonya için test edilmiştir. Diğer bir deyişle, bölgelerin sahip oldukları farklı karakterlerin, bölgeler arası piyasa ayrışması/bütünleşmesi derecelerinde farklılıklara neden olduğu hususu dikkate alınarak; varlık fiyatlama modellerinin bölgesel versiyonları kullanılmıştır. Elde edilen bulgular, getiri aralığı ve diğer tüm volatilite ölçütlerinin Avrupa, Asya-Pasifik, Güney Amerika, ODKA ve Japonya'da; maksimum ve minimum getiri anomalilerinin ise her bir coğrafi bölgede etkili olduğunu göstermektedir. Buna ek olarak, büyüklük ve değer etkilerinin Japonya dışında her bölgede; Japonya'da ise sadece büyüklük etkisinin anlamlı olduğu sonucuna varılmıştır. Momentum etkisinin Kuzey Amerika, Avrupa ve ODKA; karlılık etkisinin ise ölçüm metoduna bağlı olarak Avrupa ve Asya-Pasifik; çarpıklık ölçülerinin ise sadece Avrupa yerel endüstri endeksleri getirilerini anlamlı bir şekilde etkilediği görülmektedir. Son olarak, portföy analiz sonuçlarının büyük bir çoğunluğu Fama-MacBeth regresyonları ile desteklenmektedir.

Üçüncü bölümde, değer etkisi ölçütü olan Kazanç/Fiyat değeri (*KF*) oranı, Fama ve French (2008)'in çalışmasındaki ayrıştırma yöntemi izlenerek; gecikmeli *KF* değeri, kazançtaki değişim, momentum ve zıtlık etkisi olmak üzere 4 bağımsız bileşene ayrıştırılmıştır. İkinci bölümde kullanılan yerel endüstri endeksleri örneklemine ek olarak, 51 ülke endeksi de kullanılmıştır. Elde edilen bulgular her iki örneklem için de anlamlı bir *KF* oranı etkisinin var olduğunu; *KF* oranı bileşenlerinin, *KF* oranının sahip olduğu bilgi setinden bağımsız bilgiler içerdiği ve bu bilgilerin de gelecek getiri oranları tahminlerini anlamlı bir şekilde geliştirdiğini göstermektedir. Ayrıca, *KF* oranı ayrıştırmasının Güney Amerika dışında tüm bölgelerin yerel endüstri endeksleri için anlamlı olduğu tespit edilmiştir. Bununla birlikte, ilgili bulguların, gecikmeli *KF* oranının hesaplanmasında kullanılana gecikme uzunluğuna bağlı olarak değişebileceği saptanmıştır. Son olarak, her iki örneklemin piyasa değeri bazlı portföyleri için uygulanan ayrıştırma analizleri, *KF* oranı ayrıştırmasının düşük piyasa değerli endeksler için daha fazla bilgi ortaya çıkardığını göstermektedir.

Anahtar Kelimeler: portföy yönetimi, uluslararası yatırımcılar, varlık fiyatlama, Fama-MacBeth regresyonları, volatilite ölçütleri, endeks getirileri, getiri tahmin edilebilirliği, değer etkisi, ayrıştırma.

ACKNOWLEDGEMENTS

Firstly, I would like to thank my supervisor Assoc. Prof. (PhD) Mehmet Umutlu for his guidance and patience throughout my dissertation study. He always supported me to improve all different aspects of my analyses and drafts in every step of my doctoral study.

I would also like to thank Assoc. Prof. (PhD) Ebru Saygılı and Assist. Prof. (PhD) Hakan Özkaya for their constructive comments and suggestions to improve the quality of this dissertation.

I am thankful to the other members of my dissertation committee, Assoc. Prof. (PhD) Adam Zaremba and Assoc. Prof. (PhD) Mehmet Oğuz Karahan, for their helpful comments.

I want to send my special thanks to Prof. (PhD) Eugene F. Fama and Prof. (PhD) Kenneth R. French, who relentlessly contribute to the finance literature with their invaluable studies.

I am thankful to be supported by the Scientific Research Council of Turkey (TÜBİTAK) 2211-A National PhD Scholarship Program (2211-A Genel Yurtiçi Doktora Burs Programı) through my doctorate.

Finally, I am deeply grateful to my family for their unconditional and endless love, care, support, and patience throughout my life. This dissertation could never emerge without them. This thesis is dedicated to them.

Pelin Bengitöz

İzmir, 2021

TEXT OF OATH

I declare and honestly confirm that my study, titled "ESSAYS ON INTERNATIONAL PORTFOLIO INVESTMENTS" and presented as a PhD Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Pelin Bengitöz

02.04.2021

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
FF3	Fama-French Three-factor Model
FFC4	Fama-French-Carhart Four-factor Model
FM	Fama-MacBeth
FTSE	Financial Times Stock Exchange
HML	High-minus-Low
ICAPM	International Capital Asset Pricing Model
ICB	Industry Classification Benchmark
MENA	Middle East and South Africa
SMB	Small-minus-Big
WML	Winner-minus-Loser

INTRODUCTION

The finance literature investigates cross-sectional patterns in asset returns because potential return predictors play important roles in the construction of trading strategies. Recent studies indicate that, beyond systematic risk, which was the only significant return predictor in the Capital Asset Pricing Model (CAPM, Sharpe, 1964; Lintner, 1965; Mossin, 1996), there are several indicators of the cross-section of expected returns at the stock level[1].

The more the popularity of global investment has increased due to the benefits of international diversification, the more global portfolios have grown (Wang, Lee, & Huang, 2003; Phylaktis & Xia, 2006; Moerman, 2008). Moreover, since rational asset-pricing models have also lost their ability to predict index returns, there are also stock level anomalies at the index level, such as size, value, and momentum[2]. While index level studies have mainly focused on country indexes (Richards, 1997; Bhojraj & Swaminathan, 2006; Bali & Cakici, 2010; Liu, Liu, & Ma, 2011; Kim, 2012; Hueng, 2014; Zaremba, 2015), recent studies have demonstrated the significant predictive ability of stock level anomalies in industry indexes (Boudoukh, Richardson, & Whitelaw, 1994; Moskowitz & Grinblatt, 1999; Baca, Garbe, & Weiss, 2000; Ferreira & Ferreira, 2006; Umutlu, 2015; Zaremba & Umutlu, 2018; Zaremba, 2020; Umutlu & Bengitöz, 2020). As correlations between country indexes have increased due to globalization, diversifying across

---

[1] Some stock level studies and the anomalies they focus on include the following: Scholes & Williams (1977) – Beta; Merton (1987), Malkiel & Xu (2004), and Ang, Hodrick, & Zhang (2006, 2009) – Idiosyncratic Volatility; Litzenberger & Ramaswamy (1979) – Dividend Yield; Banz (1981) – Size; Basu (1983) – Price-Earnings Ratio; Jegadeesh & Titman (1993) and Carhart (1997) – Momentum; Lehmann (1990), and Jegadeesh (1990) – Reversal; Harvey & Siddique (2000) – Skewness measures; Bali, Cakici, & Whitelaw (2011) – MAX and Skewness measures; Fu, Arisoy, Shackleton, & Umutlu (2015) – Option-implied volatilities.

[2] Some index-level studies and the anomalies they focus include the following: Chan, Jegadeesh, & Lakonishok (1996), Chan, Hameed, & Tong (2000), Desrosiers, L'Her, & Plante (2004), Bhojraj & Swaminathan (2006), and Liu, Liu, & Ma (2011) – Momentum; Keppler & Encinosa (2011) – Size; Kim (2012) – Value; Moskowitz & Grinblatt (1999) and Asness, Moskowitz, & Pedersen (2013) – Momentum and Value; Zaremba (2015) – Value, Size, and Momentum; Zaremba (2016a) – Low Risk Anomaly.

countries has provided less risk reduction (Goetzmann, Li, & Rouwenhorst, 2005; Bekaert & Mehl, 2017). Therefore, diversification across industries is more suitable for international investors, although the number of industry level studies are very few and the predictive ability of the index level versions of the stock level anomalies still requires investigation.

The first chapter addresses the question of whether measures of volatility, skewness, momentum, profitability, and size and value effects, as well as some stand-alone measures can also be used as return predictors of international indexes. It is also the first time that the predictive ability of *Range*, which is offered as a proxy for total volatility, has been examined for international index returns. The country-industry indexes are used as an international sample. The analysis includes the following nineteen index attributes: *Range*, the difference between maximum and minimum daily index returns within a month; *MAX*, the maximum daily index return within a month; *MIN*, the negative of the minimum daily index return within a month; *SD*, the standard deviation of index returns; *IVOL*, the index-specific idiosyncratic volatility; *BETA*, the market beta obtained from the ICAPM; *TSKEW*, the total skewness of the index returns; *ISKEW*, the idiosyncratic skewness; *MV*, the market capitalization; *EP*, the earnings-to-price ratio; *DY*, the dividend yield; *EBITDA/EV*, the cash earnings before interest, tax, depreciation, and amortization divided by the enterprise value; *IntMom*, the intermediate-term momentum; *StMom*, the short-term momentum; *OP*, the operating profitability; *ES*, the earnings surprise; *ROE*, the return on equity; *INV*, the investment; and *NSI*, the net share issuance. In summary, the first chapter investigates the explanatory power of *Range* as well as the previously documented stock level anomalies at the index level. The significance of trading strategies based on these index attributes is also examined under the control of the size effect.

The second chapter investigates the significance of the nineteen index attributes, including the newly proposed total volatility measure of *Range*, on a regional basis by dividing the extended sample of country-industry indexes into six different regions: North America, Europe, Asia-Pacific, South America, MENA (Middle East and North Africa), and Japan. Several studies have demonstrated that the significance of return predictors varies across regions and stock markets due to their financial market development and market segmentation/integration[3]. The first chapter assumes that the total sample of the county-industry indexes are fully integrated with the global market. It therefore uses the international versions of the asset-pricing models. In contrast, the second chapter considers the different characteristics of regions regarding their stock market conditions, market regulations, and economic activities, which define the degree of their market segmentation/integration. Thus, it uses the regional versions of the asset-pricing models (Bekaert, Hodrick, & Zhang, 2009). These regional asset-pricing models adjust index returns to both global and regional risk factors.

The efficiency of trading strategies based on these index attributes are examined by performing both portfolio-level analyses and index-level cross-sectional regressions for the total sample and regions of the country industry-indexes. The first chapter also investigates the size effect on the behavior of the index attributes by performing bivariate portfolio sorts based on size and the other eighteen index attributes and index-level cross-sectional regressions for the different size segments. In the first chapter, the risk-adjusted returns from the portfolio analyses are estimated using the international versions of the asset-pricing models, which are the International CAPM (ICAPM), the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4). In the second chapter, the regional versions of these asset-pricing models are performed. Lastly, in the first chapter, the conditional relation between the total volatility measures of *Range* and *SD* is examined by performing bivariate portfolio analyses on each other.

The strong correlations between the return range, the newly proposed proxy of total volatility, and the standard deviation, the traditional measure of total volatility, and the strong predictive power of the return range on index returns suggest that the return range can be used as a practical measure of total volatility rather than the standard deviation. Moreover, the size effect also has a crucial effect on the relationship between index returns and index attributes. The results of the first chapter indicate that return range, standard deviation, and idiosyncratic volatility significantly affect the returns on small-cap indexes.

---

[3] Some studies focused on market segmentation/integration include the following: Errunza & Losq (1985), Bekaert & Harvey (1995), Foerster & Karolyi (1999), Bekaert, Harvey, & Lumsdaine (2002), De Jong & De Roon (2005), Carrieri, Errunza, & Hogan (2007), Umutlu, Akdeniz, & Altay-Salih (2010a), Umutlu, Altay-Salih, & Akdeniz (2010b), Bekaert, Harvey, Lundblad, & Siegel (2011), Hou, Karolyi, & Kho (2011), Zaremba (2016c), Umutlu & Bengitöz (2020).

The maximum and minimum return anomalies persist across all size quintiles, although they are stronger for small-cap indexes. Moreover, skewness measures have significant effects in small-size portfolios, the momentum measures in small- and medium-size portfolios, the profitability measures in small- and large-size portfolios, and the value measures in all portfolio sizes. The significance of these measures may vary depending on their definitions across size segments. The results presented in the second chapter indicate that all volatility measures and the return range significantly affect the returns of the country-industry indexes from Europe, Asia-Pacific, South America, and Japan. In addition, the maximum and minimum return anomalies have consistently significant effects on index returns regardless of the region. Moreover, there are significant size and value effects for all regions except for Japan, which only has a size effect. The momentum effect has a significant explanatory power for North America, Europe, and MENA. Depending on the measurement approach, the profitability effect generates abnormal returns in Europe and Asia-Pacific. Furthermore, the skewness measures only significantly affect the returns of European country-industry indexes. Lastly, most of the results of the portfolio analyses are supported by the Fama-MacBeth regressions.

The relationship between expected stock returns and the value effect has also been widely documented in the finance literature. Basu (1977, 1983), who provided fundamental research into the value effect, argues that portfolios that include stocks with low price-to-earnings (*PE*) ratio stocks yield higher average risk-adjusted returns than portfolios with high *PE* ratio stocks. Globalization has also focused attention on investigating the value effect on the returns of country and industry indexes. These international level studies also indicate that indexes with high *EP* ratios outperform those with low *EP* ratios (Macedo, 1995; Kim, 2012; Angelidis & Tessaromatis, 2014; Zaremba, 2016b; Umutlu & Bengitöz, 2020).

The third chapter addresses the question of whether the decomposition methodology of Fama and French (2008), which is adapted to the *EP* ratio, does matter for the returns on both country-industry indexes and country indexes. The analyses in this chapter extends previous studies of the value effect to an international level while also being the first study to decompose the *EP* ratio at the index level into four components, namely momentum, reversal, change in earnings, and lagged *EP*. The analysis determines whether the *EP* ratio components reveal additional information that can improve the estimation of returns from both country-industry and country indexes. In addition, the analysis tests the validity of *EP* decomposition for various time horizons of the lagged value of the *EP* ratio. Lastly, the decomposition analyses are performed for developed and emerging markets, across six regions, and different size portfolios in order to evaluate the validity of the *EP* decomposition across sub-samples.

The results show that the *EP* ratio has significant explanatory power on the returns of both country-industry and country indexes in most cases. This implies that indexes with high *EP* ratios perform better than those with low *EP* ratios. In addition, decomposing the *EP* ratio into its components reveals additional information that provides more accurate estimates of expected returns for both country-industry and country indexes. Moreover, decomposition of *EP* matters for all regions for country-industry indexes except South America. However, these results vary depending on the time horizons used for the lagged value of *EP*. Lastly, the decomposition analyses for the size-based portfolios of country-industry and country indexes show that the *EP* components provide more information for small-cap indexes.

The dissertation is organized as follows. Section 1 investigates the relationship between several return predictors, including the newly proposed total volatility measure of *Range*, and the expected returns at the international index level. Section 2 re-examines this relationship on a regional basis by using more recent data from more countries. Section 3 decomposes the *EP* ratio at the international index level while Section 4 draws on the previous chapters to reach the overall conclusion of the dissertation.

CHAPTER 1
THE CROSS-SECTION OF EXPECTED INDEX RETURNS IN INTERNATIONAL STOCK MARKETS

1.1. Introduction

The aim of this chapter is to identify and understand cross-sectional patterns in expected international index returns, which is always an important issue in investment analysis. Traditional asset pricing theories, which were mainly developed by Sharpe (1964), Lintner (1965), and Mossin (1966), known as the Capital Asset Pricing Model (CAPM), assume that only systematic risk affects expected stock returns because unsystematic risk can be diversified away. In contrast to such rational asset pricing models, recent studies show that several anomalies can affect the cross-section of expected returns at the stock level[4].

The benefits of international diversification make global investment more attractive. Thus, global investments have become pervasive among international investors (Wang, Lee, & Huang, 2003; Phylaktis & Xia, 2006; Moerman, 2008), who aim to decrease portfolio risk through international diversification. To accomplish this, it is important to determine the potential indicators of index returns. As global investment has become pervasive among international investors, rational asset-pricing models have become impractical to explain the systematic determinants of international index returns. Recent studies show that effects of size, value, and momentum, which are mainly documented at the stock level, are also documented at the index level[5]. Studies related to traditional asset pricing models and

---

[4] Some stock level studies and the anomalies they focus on include the following: Scholes & Williams (1977) – Beta; Merton (1987), Malkiel & Xu (2004), and Ang, Hodrick, & Zhang (2006, 2009) – Idiosyncratic Volatility; Litzenberger & Ramaswamy (1979) – Dividend Yield; Banz (1981) – Size; Basu (1983) – Price-Earnings Ratio; Jegadeesh & Titman (1993) and Carhart (1997) – Momentum; Lehmann (1990), and Jegadeesh (1990) – Reversal; Harvey & Siddique (2000) – Skewness measures; Bali, Cakici, & Whitelaw (2011) – MAX and Skewness measures; Fu, Arisoy, Shackleton, & Umutlu (2015) – Option-implied volatilities.

[5] Some of the index level studies and the anomalies they focus on are as the following: Chan, Jegadeesh, & Lakonishok (1996), Chan, Hameed, & Tong (2000), Desrosiers, L'Her, & Plante (2004), Bhojraj & Swaminathan (2006), Liu, Liu, & Ma (2011), and Zaremba, Umutlu, & Karathanopoulos (2019) –

recent studies have paved the way for further investigation of recently documented stock level anomalies at the index level.

While many index level analyses examined the effects of these stock level anomalies for country indexes (Richards, 1997; Bhojraj & Swaminathan, 2006; Bali & Cakici, 2010; Liu, Liu, & Ma, 2011; Kim, 2012; Hueng, 2014; Zaremba, 2015), recent studies have started to focus on industry indexes as well (Zaremba and Umutlu, 2018; Zaremba, 2020). These recent studies show that some stock level anomalies significantly affect industry indexes (Boudoukh, Richardson, & Whitelaw, 1994; Moskowitz & Grinblatt, 1999; Baca, Garbe, & Weiss, 2000; Ferreira & Ferreira, 2006; Umutlu, 2015; Umutlu & Bengitöz, 2020). Furthermore, correlations among country indexes have increased due to globalization, so diversifying across countries provides less risk reduction than before (Goetzmann, Li, & Rouwenhorst, 2005; Bekaert & Mehl, 2017). These developments make diversification across industries more appropriate for international investors. However, very few index level studies have examined the predictability of industry index returns.

This chapter addresses the question of whether the stock return predictors, such as volatility measures, skewness measures, size, value, and momentum effects, profitability measures, and several stand-alone measures, can also explain international index returns. In this chapter, I also suggest a novel return predictor called *Range*, which proxies for total volatility, and examine its predictive power for international index returns. More specifically, I investigate whether the trading strategies based on *Range* and the index level analogs of recently documented and traditional stock attributes, whose effects on stock returns are mostly proven previously, generate abnormal returns for international investors. Country-industry indexes are used for the international sample, which provides more international assets than country indexes can. The nineteen index attributes are as follows: *Range* is the difference between maximum and minimum daily index returns within a month; *MAX* is the maximum daily index return within a month; *MIN* is the negative of the minimum daily index return within a month; *SD* is the standard deviation

---

Momentum; Keppler & Encinosa (2011) – Size; Kim (2012) – Value; Moskowitz & Grinblatt (1999), and Asness, Moskowitz, & Pedersen (2013) – Momentum and Value; Zaremba (2015) – Value, Size, and Momentum; Zaremba (2016a) – Low Risk Anomaly; Umutlu (2015, 2019) – Idiosyncratic volatility.

of index returns; *IVOL* is the index-specific idiosyncratic volatility; *BETA* is the market beta obtained from the ICAPM; *TSKEW* is the total skewness; *ISKEW* is the idiosyncratic skewness; *MV* is the market capitalization; *EP* is the earnings-to-price ratio; *DY* is the dividend yield; *EBITDA/EV* is the cash earnings before interest, tax, depreciation, and amortization divided by the enterprise value; *IntMom* is the intermediate-term momentum; *StMom* is the short-term momentum; *OP* is the operating profitability; *ES* is the earnings surprise; *ROE* is the return on equity; *INV* is the investment; and *NSI* is the net share issuance. The effects of operating profitability and investment were recently examined by Fama and French (2006, 2015); earnings surprise and return on equity by Hou, Xue, and Zhang (2015); net share issuance by Fama and French (2008); and maximum and minimum return anomalies by Bali, Cakici, and Whitelaw (2011). In sum, this chapter focuses on the predictive ability of *Range* and both recently documented and traditional stock-level anomaly variables at the index level after controlling for several variables. The significance of the predictive abilities is also tested across indexes of different sizes to investigate the varying performance of index attributes across size segments.

The chapter evaluates the profitability of trading strategies based on *Range* and other index attributes by performing both portfolio-level analyses and index-level cross-sectional regressions. Firstly, a portfolio-level analysis is conducted by sorting international indexes based on each index attribute. If the zero-cost trading strategy based on these index attributes works, then portfolios containing different levels of an index attribute should provide statistically significant different returns. Accordingly, I test whether the raw and risk-adjusted returns on high minus low attribute portfolios are significantly different from zero. I also investigate whether the effect of an index attribute on returns can be driven by the size effect. Next, Fama-MacBeth cross-sectional regressions are conducted to test whether the relevant index attribute significantly affects future index returns. The regression analysis enables the effects of several index attributes to be evaluated simultaneously. I also test the results of the index-level cross-sectional regression for different size quintiles of the country-industry indexes. Lastly, I examine the conditional relationship between the total volatility measures of *Range* and *SD* by performing bivariate portfolio analyses each other.

The strong correlation between range and the standard deviation, and the strong predictive power of range on index returns suggest that range can be used as a practical measure of total volatility rather than the traditional measure of standard deviation. Moreover, the results show that index size has a crucial impact on the relationship between index returns and index attributes. The univariate and bivariate portfolio sorts, and Fama-MacBeth regressions for the whole sample and size-based sub-samples generally indicate that range, standard deviation, and idiosyncratic volatility significantly affect the returns on small-cap indexes. On the other hand, maximum and minimum return effects are independent of index size since they are prevalent across all size quintiles but stronger for small-cap indexes. Moreover, there is a value effect for almost all size segments, from small to large, depending on the different measures of the value effect. The profitability measure of return on equity and skewness measures exist especially in small-cap portfolios, the momentum effect in both small-cap and medium-cap portfolios, and the profitability measure of earnings surprise exclusively in large-cap portfolios. Conversely, beta, operating profitability, and investment values fail to affect index returns for all size segments. Lastly, net share issuance affects mixed portfolio sizes.

The first chapter is organized as follows. Section 1.2 describes the data and its sources. Section 1.3 summarizes the anomalies. Section 1.4 describes the methodologies for the portfolio-level analyses and the index-level cross-sectional regressions. Section 1.5 presents the results of the analyses. Section 1.6 concludes.

1.2. Data

In this dissertation chapter, the data for the local industry indexes are downloaded from Datastream, which provides DS Global Indices. The dataset includes daily and monthly dollar returns for local industry indexes. In addition to return data, Datastream also provides market value, price-to-earnings ratio, dividend yield, return on equity, and enterprise value over earnings before interest, taxes, depreciation, and amortization for local industry indexes. Moreover, some additional data such as price index, earnings before interest and tax, total assets, shareholders' equity, interest charge over, the 12-month forward earnings per share, are also downloaded to calculate some anomalies. The world market portfolio, which is used in the asset-pricing models, is represented by the

World Market Index from Datastream. Lastly, daily and monthly risk-free rates are obtained by using daily and monthly Eurodollar deposit rates from Datastream.

The research period generally extends from January 1973 to July 2015 for the monthly analyses and from January 1, 1973 to July 31, 2015 for the daily analyses. The market capitalization, price-to-earnings ratio, dividend yield; return on equity, earnings before interest, taxes, depreciation, and amortization over enterprise value, price index, and the 12-month forward earnings per share values are obtained in a monthly basis while the return data in both daily and monthly basis. On the other hand, some accounting data such as earnings before interest and tax, total assets, shareholders' equity, earnings per share, interest charge over are obtained annually to construct some of the anomalies. Therefore, the earliest starting date for the anomalies using monthly data is January 1973 while for the anomalies using annual accounting data is June 1983.

The main sample is the local industry indexes and local *supersector* indexes are employed to track local industry portfolios. Each of the local *supersector* index is employed as an individual international asset, which is used by international investors in trading strategies. The Industry Classification Benchmark (ICB) of Financial Times Stock Exchange (FTSE)[6] summarizes the *supersector* definitions. *Supersector* indexes include the companies that share the similar industrial themes. With reference to the ICB, there are 19 *supersectors* and these *supersectors* are classified based on 37 countries, which 23 are developed and 14 are emerging or developing. Since some *supersector* data for some countries cannot be obtained from Datastream, there are 673 different local industry indexes rather than the total number of 703 (19*37). The 19 *supersectors* indexes are as the following; Automobile & Parts, Banks, Basic Resources, Chemicals, Construction & Mat., Financial Services, Food & Beverages, Health Care, Ind. Goods & Svs., Insurance, Media, Oil & Gas, Pers. & H/H Goods, Real Estate, Retail, Technology, Telecom, Travel & Leisure, and Utilities. Moreover, the 37 countries are as the following: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherland, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, UK, USA as developed countries; Argentina, Brazil, Chile, China,

[6] The supersector definitions and the ICB structure are comprehensively documented in the following link: www.icbenchmark.com.

India, Korea, Malaysia, Mexico, Philippine, Poland, South Africa, Taiwan, Thailand, Turkey as developing/emerging countries.

The advantages of using *supersector* indexes as the main sample are twofold. First, globalization and financial liberalization processes make the degree of integration high and increase correlation among countries and therefore, the opportunity of international diversification across countries is getting weaker. Weiss (1998) states that instead of country level approaches, industry level approaches may provide more detailed information about global equity management. Recent studies provide empirical evidence on behalf of this view by showing that besides country effects, industry effects are also important in valuing and controlling risk of global assets (Baca et al., 2000; Umutlu, 2015; Zaremba & Umutlu, 2018; and Umutlu & Bengitöz, 2020;). Second, *supersector* indexes provide higher number of international assets (673 local supersector indexes to be more specific) than country indexes, which generally include less than hundred countries. The high number of cross-sectional units enhances the power of the analyses for *supersector* indexes.

1.3. Anomalies

Anomalies are defined as the patterns in the security returns and contradict with the efficient market hypothesis (EMH). In other words, anomalies exist when the EMH is a failure. The EMH, which is proposed by Fama (1970), states that investors just wash a brick by performing trading strategies such as purchasing undervalued stocks or selling at inflated prices in the aim of beating the market. According to the EMH, stocks are always at their fair levels, where the true returns are provided with respect to the risk of the relevant stock since all available information about that stock is already reflected by the stock prices. Stock prices can only be changed by the existence of a new information, which must be unpredictable. This argument implies that prices should follow random walk; prices should change randomly and unpredictably (Bodie, Kane, & Marcus, 2010:229-232). However, empirical studies pointed out that the real world contradicts with the EMH because of its strict assumptions and show that there are several anomalies significantly affect stock returns.

In this dissertation chapter, I aim to examine the predictive ability of nineteen anomalies, which are the newly-proposed *Range* effect as well as the widely used and newly-documented stock level anomalies, at the index level. The main focus of potential predictors are the volatility measures, skewness measures, measures of size and value effects, measures of momentum effects, profitability measures, and lastly, the stand-alone variables of investment and net share issuance. In the construction of these anomalies, monthly and daily individual international index returns and some additional variables are used.

1.3.1. Volatility Measures

The first group of variables is related with the volatility measures. I examine systematic, idiosyncratic, and total volatility. Capital Asset Pricing Model (CAPM), which is developed by Sharpe (1964), Lintner (1965), and Mossin (1966), indicates that the expected return of any security changes depending on the return on riskless security, market beta of that security, and the market risk premium. According to the CAPM, it is stated that the cross-sectional variation in the expected return of any security is only explained by the cross-sectional variation in the beta of that security. Being beta as the single return predictor is widely tested in the empirical asset pricing literature. Earlier studies point out that beta has positive effect on the cross-sectional future stock returns (Blume & Friend, 1973; Fama & MacBeth, 1973). However, recent studies reject that inference by finding no positive relation between beta and future stock returns (Reinganum, 1981; Lakoniskok & Shapiro, 1986; Fama & French, 1992, 1993; Bali, Brown, Murray, & Tang, 2017; Frazzini & Pedersen, 2014; Zaremba, 2016b). The systematic risk, *BETA*, is estimated in a monthly basis by using available daily return data in that month with the International CAPM (ICAPM) formula shown in Equation (1.1). The market beta for an individual international index is the estimated regression coefficient $\hat{\beta}_{1i}$ (Bali et al., 2011; Bali, Engle, & Murray, 2016:122-123).

$$R_{idt} - r_{fdt} = \alpha_{it} + \beta_{1i}\left(R_{mdt} - r_{fdt}\right) + \varepsilon_{idt} \tag{1.1}$$

where R_{idt} is the return on *i*. individual international index on day *d* in month *t*, R_{mdt} is the world market (represented by the Datastream World Market Index) return on day *d* in month *t*, and r_{fdt} is the risk-free rate on day *d* in month *t*.

Levy (1978) and Merton (1987) develop models to soften the restrictive assumptions of CAPM and Arbitrage Pricing Theory (Ross, 1976). They also price firm-specific risk and find that there is a positive relation between firm-specific risk and future stock returns. On the other hand, Ang, Hodrick, Xing, and Zhang (2006, 2009) find that there is a negative relation between idiosyncratic risk and international stock markets. Fu (2009) indicate that idiosyncratic volatility positively affects future stock returns. Huang, Liu, Rhee, and Zhang (2009) and Guo, Kassa, and Ferguson (2014) state that this relation is negative. Bali, Cakici, and Whitelaw (2011) points out that in some cases the negative relation disappears and, in some cases, there exist positive relation between idiosyncratic volatility and future stock returns (Bali et al., 2016:363-365). Differently, Umutlu (2015) examines idiosyncratic volatility at the global level and find no relation with international index returns.

In this dissertation chapter, *IVOL* represents the idiosyncratic volatility, which is calculated by taking the standard deviation of the error terms obtained by performing the ICAPM shown in Equation (1.1). The monthly idiosyncratic volatility for *i.* individual international index in month *t* is estimated as indicated in Equation (1.2) (Bali et al., 2011):

$$IVOL_{it} = \sqrt{\sum_{d=1}^{D} (\varepsilon_{idt})^2} \tag{1.2}$$

where ε_{idt} is the error term on day d in month t and D is the number of trading days in month t.

In addition to *IVOL*, the total volatility, which is also a function of CAPM as idiosyncratic risk and systematic risk, is also taken into account. The traditional total volatility measure of standard deviation, *SD*, is estimated in a monthly basis and it is the standard deviation of available daily return data within a month. *SD* is mathematically calculated as (Bali et al., 2011):

$$SD_{it} = \sqrt{\frac{\sum_{t=1}^{n} (R_{idt} - \bar{R}_{it})^2}{n-1}} \sqrt{n} \tag{1.3}$$

where R_{idt} is the return on *i*. individual international index on day *d* in month *t*, $\bar{R}_{it}$ is the average return of daily index returns of *i*. individual international index in month *t*, *n* is the number of trading days in month *t*. The multiplication factor of $\sqrt{n}$ is used to convert the standard deviation of the periodic returns to a monthly value.

Range, which is offered as an alternative proxy for the total volatility, is defined as the difference between maximum and the minimum daily returns within a month.

MAX and *MIN* are also defined as the measures of total volatility. *MAX* represents the maximum daily return within a month and used as a proxy for upside risk (Bali et al., 2011). Similarly, *MIN* represents the negative of the minimum daily return within a month and used as a proxy for downside risk.

1.3.2. Skewness Measures

This group of variables captures skewness measures. Arditti (1967, 1971) focuses on the skewness of returns, which is also defined as the third moment of returns, in obtaining optimal investment decisions. Arditti (1967, 1971) states that the investors with the negatively skewed return distributions expect a higher rate of return on their investments. Harvey and Siddique (2000) indicate that not only systematic skewness, but also conditional co-skewness is priced in the security expected returns. Simkowitz and Beedles (1978), Conine Jr. and Tamarkin (1981), and Mitton and Vorkink (2007) obtain that there is a significant effect of idiosyncratic skewness on asset prices. Boyer, Mitton, and Vorkink (2010) obtain strongly negative cross-sectional relation between idiosyncratic skewness and future stock returns (Bali et al., 2016:319-320). Bali et al. (2011) and Zaremba (2016b) also find that skewness measures negatively affect future stock returns.

The literature has several different approaches about estimation techniques of skewness measures. However, I only present the estimation techniques for total skewness and idiosyncratic skewness. The skewness measures used in this study are conditioned on the information of the past one year of daily data. Total skewness (*TSKEW*) is estimated in a monthly basis following the study of Bali et al. (2011):

$$TSKEW_{it} = \frac{1}{D_t}\sum_{d=1}^{D_t}\left(\frac{R_{id}-\mu_i}{\sigma_i}\right)^3 \tag{1.4}$$

where D_t shows the number of trading days spreading from months *t*-12 to *t*-1, R_{id} shows the return on *i*. international index on day *d*, μ_i shows the mean of daily returns on *i*. international index from months *t*-12 to *t*-1, and σ_i shows the standard deviation of daily returns on *i*. international index from months *t*-12 to *t*-1.

The monthly values of idiosyncratic skewness (*ISKEW*) are estimated with daily data by partitioning total skewness into two constituents, which are idiosyncratic and systematic skewness as shown in Equation (1.5):

$$R_{id} - r_{fd} = \alpha_i + \beta_i\left(R_{md} - r_{fd}\right) + \gamma_i\left(R_{md} - r_{fd}\right)^2 + \varepsilon_{id} \tag{1.5}$$

where R_{id} is the daily return on index *i*, R_{md} is the daily world market return, r_{fd} is the daily risk-free rate, and ε_{id} is the daily idiosyncratic return on day *d*. For each month, Equation (1.5) is performed by using the daily data of the previous 12-month period covering months from *t*-12 to *t*-1. The *ISKEW* of index *i* in month *t* is the skewness of daily residuals, ε_{id}, in Equation (1.5) from the previous year.

1.3.3. Size and Value Measures

The third group of variables is the measures of size and value effects. The size effect, which is one of the fundamental finding in the empirical asset pricing theory, states that stocks that have large market capitalization values outperform the stocks that have small market capitalization values, vice versa (Banz, 1981; Lakonishok & Shapiro, 1986; Fama & French, 1992, 1993). In addition to stock level analysis, the size effect is also examined at the country level. It is found that firms, which have low market capitalization values, performs better than the firms, which have high market capitalization values (Keppler & Traub, 1993; Asness, Liew, & Stevens, 1997; Keppler & Encinosa, 2011; Zaremba, 2016b). The monthly market capitalization values are directly obtained from the Datastream. In this dissertation chapter, *MV* represents for the market capitalization, which is calculated as the multiplication of the share price by the number of ordinary shares. *MV* is expressed in billion dollars in Datastream.

There are several studies showed that stocks having low prices related with earnings (Basu, 1977, 1983; Jaffe, Keim, & Westerfield, 1989), dividends (Lakonishok, Shleifer, & Vishny, 1994) generate higher long-run returns than the stocks (growth stocks) having high prices related with these measures of value. Moreover, Fama and French (1992) mainly concentrate on market capitalization and book-to-market ratio, and summarize the relation of them with future stock returns. The price-to-earnings (*PE*) ratio effect, documented by Basu (1977, 1983), means that portfolios with low *PE* ratio stocks generate greater average risk-adjusted returns than portfolios with high *PE* ratio stocks. Earlier studies also suggest that some value ratios help explain the cross-sectional variation of country or industry indices (Macedo, 1995). Angelidis and Tessaromatis (2014) state that stocks with high dividend yield outperform the stocks with low dividend yield and the stocks that have low *PE* ratio outperform the stocks that have high *PE* ratio. Moreover, Kim (2012) focuses on three variables (the earnings yield spread, the earnings growth dispersion, and the return dispersion) to estimate the intra-country time variation in the value premium and examines whether these variables can be used to forecast the inter-country cross-sectional variations in the value premium. Zaremba (2016b), who examines the effect of fifty different stock related variables on expected returns at the country level, finds consistent results for *PE* ratio and dividend yield with the study of Angelidis and Tessaromatis (2014). The monthly values of *PE* ratio and dividend yield (*DY*) are directly obtained from the Datastream. I focus on earnings-to-price (*EP*) ratio, which is directly the reverse of the *PE* ratio. *EP* ratio is the division of the earnings per share to the share price. *DY* expresses the dividend per share as a percentage of the share price.

Sloan (1996) states that firms having high value of accruals can generate lower abnormal returns on average compared to firms having low value of accruals. Sloan (1996) calculates accruals as the difference between the changes in current assets and cash/cash equivalents. Sloan (1996) also excludes debt in current liabilities and income taxes payable from accruals. Moreover, Stambaugh, Yu, and Yuan (2012) obtain accruals by taking difference between noncash working capital and depreciation expense and scaled by the average of the total assets from the previous two fiscal years. However, Datastream does not have detailed accounting variables for the local industry indexes. Therefore, accruals cannot be calculated as explained in the literature. On the other hand, Datastream includes *Enterprise Value/EBITDA*, where enterprise value is the sum of market capitalization on fiscal year-end date, preferred stock, minority interest and total debt minus cash; *EBITDA* is the earnings before interest expense, income taxes, depreciation, and amortization. In this dissertation chapter, I use *EBITDA/EV* as a measure of value effect, which is the reverse of the *Enterprise Value/EBITDA*.

1.3.4. Momentum Measures

The fourth group of variables are related to momentum effects. The ability of the previous stock returns to explain future stock returns is a widely examined phenomena. The fundamental study of momentum effect is developed by Jegadeesh and Titman (1993), who proposed the medium-term momentum effect. According to the medium-term momentum, the well-performed stocks in the previous months from 6 through 12 months tend to outperform in the future. Moreover, it is also presented that the momentum effect also exists in international equity markets and in different asset classes (Chan, Hameed, & Tong, 2000; Desrosiers, L'Her, & Plante, 2004; Bhojraj & Swaminathan, 2006; Fama & French, 2012; Asness, Moskowitz, & Pedersen, 2013; Bali et al., 2011; Zaremba, 2016a).

The literature has several different approaches about estimation of the momentum effect. The momentum is measured with two different estimation techniques, which are intermediate-term and short-term momentum. The intermediate-term momentum, *IntMom*, is the cumulative monthly returns of the previous 11-month period covering months from *t*-12 to *t*-2. On the other hand, the short-term momentum, *StMom*, is the cumulative monthly returns of the previous 5-month period covering months from *t*-6 to *t*-2. The mathematically calculation of the momentum effect is defined as (Bali et al., 2016:207):

$$Momentum_{i,t} = \left[\prod_{m \in \{t-a:t-b\}} \left(R_{i,m} + 1\right) - 1 \right] \tag{1.6}$$

Where $Momentum_{i,t}$ represents *IntMom* or *StMom* for index *i* in month *t*; $R_{i,t}$ is the return of index *i* in month *t*; *a* and *b* are the limits for the months.

1.3.5. Profitability Measures

The fifth group of variables includes profitability measures. In line with the study of Fama and French (2015), operating profitability is defined as the difference between the earnings before interest and taxes (*EBIT*) and interest that is divided by the book equity. Fama and French (2015) show that there is a positive relation between operating profitability (*OP*) and future returns because higher expected earnings must be discounted by higher expected returns for a given level of market value. For every June, *OP* is calculated by using the data of the previous year's June. Each *OP* value calculated in June is kept constant until the next June, which is the month that the new *OP* value is calculated with annual data. In other words, *OP* values are rebalanced annually in every June.

Chan, Jegadeesh, and Lakonishok (1996) examine earnings momentum by using three different measures of earnings news. They find negative relation between earnings momentum and expected returns; stated that it is the reason of being analysts' forecast initially very optimistic, but later it is adjusted downward over time. Moreover, Hou et al. (2015) point out that the firms experiencing large positive earnings shocks can be more profitable than the firms experiencing large negative earnings shocks. Following these studies, earning surprise (*ES*) is defined as the changes in analysts' estimates of earnings and in line with the study of Umutlu and Bengitöz (2020), monthly values of earnings surprise are computed by using 12 Month Forward Earnings per Share (*DIEP*) and Price Index (*PI*) values from Datastream as shown in the Equation (1.7). Datastream obtains *DIEP* values from the Institutional Brokers' Estimate System (I/B/E/S).

$$ES_t = \frac{\sum_{j=1}^{6}(DIEP_{t-j} - DIEP_{t-j-1})}{PI_{t-j-1}} \tag{1.7}$$

Hou et al. (2015) measure profitability with return on equity (*ROE*) and state that *ROE*, as a risk factor, includes important information about the return variation that is not totally explained by the Fama-French model. Hou et al. (2015) show *ROE* affects the expected returns positively. Moreover, Haugen and Baker (1996) also investigate *ROE* and find similar inferences. In this dissertation chapter, *ROE* is directly obtained from Datastream in a monthly basis.

1.3.6. Investments and Net Share Issuance

Investments (*INV*) and net share issuance (*NSI*) are the stand-alone measures found to affect asset returns. Following the study of Fama and French (2015), investment is defined as the differences between the total assets from the June of year *t*-2 and the June of year *t*-1, which is divided by the total assets from the June of year *t*-2. Fama and French (2015) state that investment affects the future returns negatively. Similar with *OP*, *INV* is also calculated in June of each year and kept constant until the next June.

The last variable is the net share issuance (*NSI*). Fama and French (2008) focus on net stock issuance and some other variables by performing portfolio analyses and cross-sectional regressions. They conclude that the effect of the net stock issuance on expected returns is negative. Moreover, Stambaugh et al. (2012) and Hou et al. (2015) also find that net stock issuance affects expected returns negatively. These studies calculate net stock issuance as the growth rate of the split-adjusted shares outstanding in between the fiscal years ends *t*-1 and *t*-2. However, since the exact variable for the calculation of net stock issuance does not exist in Datastream, *NSI* is obtained by making some derivations in market capitalization value following the study of Fama and French (2008).

$$ln\left(NSI_{t-k,t}\right) = ln\left(\frac{MV_t}{MV_{t-k}}\right) - ln\left(\frac{PI_t}{PI_{t-k}}\right) \tag{1.8}$$

In the literature, since net share issuance is calculated by using values from years *t*-1 and *t*-2, *k* is taken as 12 to calculate monthly values of *NSI*. Moreover, to compute *NSI* value, I use monthly values of market capitalization (*MV*) and Price Index (*PI*) from Datastream.

1.3.7. Descriptive Statistics and Correlation Analyses

Table 1.1 shows the descriptive statistics of nineteen index attributes for country-industry indexes including 19 industries specified for 37 countries. Firstly, for each month the cross-sectional averages of the index attributes are calculated across indexes. Thereafter, the cross-sectional means are time-series averaged over the months in the whole research period. Moreover, the standard deviation, maximum, and minimum values are calculated by using the monthly time-series data of cross-sectional means. According to the basic statistics, the index attributes of *MV*, *ROE*, *ES*, *BETA*, *TSKEW*, *OP*, *ISKEW*, *EBITDA/EV*, and *INV*, which have the highest standard deviation values, correspondingly have the highest mean values. In a similar way, the range between the maximum and minimum values of these index attributes are also higher than the other attributes.

< Table 1.1 here >

Correlation matrix for nineteen index attributes for the whole sample is presented in Table 1.2. The correlation matrix for nineteen index attributes are calculated based on a method with two steps. In the first step, for each month in the sample period cross-correlations among index attributes across indexes are calculated. Then, in the second step, the cross-correlations are time-series averaged over the months in the research period and reported in Table 1.2. The results of the correlation analysis point out that the index attributes that share common themes are highly correlated. For example, there is a high correlation between *ISKEW* and *TSKEW* because idiosyncratic skewness is a component of total skewness. In addition, since the definitions of some index attributes may have a bit similarity, the pairwises of *MAX-MIN*, *EP-DY*, *IntMom-StMom*, and *OP-ROE* have high correlations between each other. Moreover, there is also a strong correlation among the volatility measures of *Range*, *SD*, *IVOL*, *MAX*, and *MIN* that should be payed attention when performing the regression analyses. These correlation results mean that the combinations of *Range–SD–IVOL-MAX-MIN*, *EP-DY*, *IntMom-StMom*, *OP-ROE*, and *ISKEW–TSKEW* should not be included in the same regression specification simultaneously to avoid the multi-collinearity problem in regression analyses.

< Table 1.2 here >

The correlation results for *Range* show that it is highly correlated with *SD* and thereafter, with *IVOL*, *MAX*, and *MIN*, respectively. Moreover, starting from the definition of *Range*, which includes both maximum and minimum returns in it, it can be suggested that *Range* combines both *MAX* and *MIN* anomalies, thus can be used as an alternative proxy for total volatility.

1.4. Methodology

1.4.1. Portfolio Analysis

Portfolio analysis is a widely used statistical methodology in the empirical asset pricing literature (Ang, Hodrick, Xing, & Zhang, 2006, 2009; Umutlu, 2015). The general aim of forming portfolio of assets is to examine both the cross-sectional variation in future returns across portfolios that have different levels of sorted variable(s) and the cross-sectional relation between the future returns and the sorted variable(s) (one or more variables). Moreover, portfolio analysis provides evidences about the potential differences in the characteristics of the assets across different levels of portfolios. In addition, portfolio analysis is also used to investigate the cross-sectional relation between one sorted variable and set of other sorted variables. Beyond these benefits of portfolio analysis, being a nonparametric technique is the most important benefit of portfolio analysis. In other words, there is no any assumption about the cross-sectional relations between the variables in the portfolio analysis. Since many methodologies require some assumptions needed to be considered, having no any assumption makes portfolio analysis performed easily (Bali et al., 2016:33). There are several forms of portfolio construction process, however, I only focus on univariate and bivariate portfolio analyses in a similar vein of Bali et al. (2016).

1.4.1.1. Univariate Portfolio Sorts

In the univariate portfolio analysis, the country-industry indexes are sorted by only one index attribute. Therefore, the cross-sectional relation between the index returns and each index attribute can be investigated.

The important decision in portfolio analysis is to determine the number of portfolios. In this dissertation, since portfolios are formed every month, this decision largely depends on the number of observations in the sample in month *t*. Using a small number of portfolios generates portfolios that have large number of indexes, thus provides weak dispersion in the sort variable across portfolios. As a result, the cross-sectional relation between index returns and the sorted attribute does not provide sensible results. On the other hand, using an appropriate number of portfolios generates portfolios that have reasonable number of indexes, thus provides increased true means of portfolios (Bali et al., 2016:35). The asset-pricing literature indicates that most of the studies use number of portfolios as between 5 and 10. In this dissertation, since the total sample of country-industry indexes has nearly 673 individual indexes, but changes across months without affecting the number of indexes in each portfolio considerably, the number of portfolios is determined as 5 to obtain sufficient portfolio analysis results.

After the determination of the number of portfolios, the univariate portfolio analysis is performed to group indexes into portfolios that have similar values of the relevant index attribute. More specifically, every month the total sample of country-industry indexes are sorted based on each index attribute. Thereafter, quintile portfolios are formed with these sorted indexes. In this stage, it is aimed that each portfolio has almost nearly the same number of indexes. As a result, portfolio 1 contains the international indexes with the lowest values of the related index attribute, while portfolio 5 contains the international indexes with the highest values.

Portfolio returns are calculated over the indexes in each portfolio for every month. More specifically, portfolio returns are calculated both by simply taking the average of the index returns in each portfolio and by taking the weighted average of the index returns according to their market capitalization values. In the next step, for every month in the sample, the equal-weighted and value-weighted portfolio returns are calculated over the next period. Thereafter, with the purpose of examining the existence of a cross-sectional relation between the sorted attribute and the portfolios returns, the time-series means of each portfolio returns are calculated over the months in the sample. It is mathematically formulated as below (Bali et al., 2016:42):

$$\bar{R}_k = \frac{\sum_{t=1}^{T} \bar{R}_{k,t}}{T} \tag{1.9}$$

$$\bar{R}_{diff} = \frac{\sum_{t=1}^{T} \bar{R}_{diff,t}}{T} \tag{1.10}$$

where $\bar{R}_{k,t}$ is the equal- or value-weighted portfolio return for the quintile portfolio of k in month t; $\bar{R}_k$ is the time-series averages of the quintile portfolio of k over the months in the sample; $\bar{R}_{diff,t}$ is the difference between the equal- or value-weighted returns of portfolios 5 and 1 in month t; $\bar{R}_{diff}$ is the time-series averages of the return differences between portfolios 5 and 1 over the months in the sample; and T is the months in the sample. The terms $\bar{R}_{diff,t}$ and $\bar{R}_{diff}$ show the returns of the zero-cost portfolios, which go long the portfolio 5 including the indexes having the highest values of an index attribute and shorts the portfolio 1 including those having the lowest values of that index attribute in month t and averaged over the months in the sample, respectively.

After portfolio formation process, it is tested that whether these long-short portfolios earn excess raw and risk-adjusted returns. Firstly, I test whether there is a statistically significant raw return differences between the time-series means of portfolio 5 and portfolio 1. More specifically, a mean difference t-test is performed between the time-series average returns on extreme value portfolios for the whole research period (510 months, first month is the portfolio formation month). Having a statistically significant nonzero mean for the difference of extreme portfolio returns implies that there is a cross-sectional relation between the sorted variable and index returns in the average time period. The hypothesis of the test is defined as

$H_0: \mu_{low} = \mu_{high}$

$H_1: \mu_{low} \neq \mu_{high}$

The null hypothesis states that the average return on portfolio 5 formed with the indexes having the highest values of the related index attribute is the same with the average return on portfolio 1 formed with the indexes having the lowest values of the related index attribute. Rejecting the null hypothesis implies that the difference between the returns on extreme portfolios is statistically significant. To put it another way, it can be concluded that portfolios located in different levels of an index attribute generate different raw returns, which means that the relevant index attribute has a role in explaining international index returns. As a result, an international investor, who longs portfolio 5 including the highest values of an index attribute and then, shorts portfolio 1 including the lowest values of that index attribute can earn raw excess returns.

In some cases, it is important to perform some additional analyses, which examine the existence of patterns in the average portfolio returns that are caused by the sensitivity of the cross-sectional variation to systematic risk factors (Bali et al., 2016:47-48). In this way, it is aimed to investigate the cross-sectional relation between the index attribute and index returns after controlling for sensitivity of the portfolios to systematic risk factors.

Beyond testing the mean difference of raw returns, it is also tested that whether the risk-adjusted returns on portfolios having extreme values are statistically different. For this purpose, it is examined that whether the Jensen alphas from several models of risk-adjustment are statistically different from zero. This type of analysis provides examining the existence of a zero-cost arbitrage portfolio for the relevant index attribute, so generates abnormal risk-adjusted returns.

The Jensen alphas, which are the returns adjusted for risk, are estimated by performing three models of risk-adjustment. These models are the International CAPM (ICAPM), and the international versions of the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4). The first model, CAPM, which is also referred as the one-factor model, is introduced by Sharpe (1964), Lintner (1965), and Mossin (1966) and includes the excess returns on the market portfolio as a market factor. The Equation (1.11) shows the mathematical form of the ICAPM:

$$R_{5-1t} = \alpha_{ICAPM} + \beta_W R_{Wt} + \varepsilon_t \tag{1.11}$$

where $R_{5\text{-}1t}$ shows the return difference between the portfolios 5 and 1 formed based on an index attribute in month t; R_{Wt} shows the excess return on world market portfolio, which is represented by the Datastream World Market Index; α_{ICAPM} is the Jensen alpha from the ICAPM; ε_t shows the error term.

The next model, the FF3 model, which is introduced by Fama and French (1993), includes both the market factor as well as two additional risk factors related with the size and value effects. The international version of FF3 model is shown in Equation (1.12):

$$R_{5-1t} = \alpha_{FF3} + \beta_W R_{Wt} + \beta_{WSMB} R_{WSMBt} + \beta_{WHML} R_{WHMLt} + \varepsilon_t \tag{1.12}$$

where R_{WSMBt}, which is referred as small-minus-big factor, shows the returns on the portfolios based on the size effect; R_{WHMLt}, which is referred as high-minus-low factor, shows the returns on the portfolios based on the value effect; and α_{FF3} shows the Jensen alpha from the international version of the FF3 model. R_{WSMBt} is defined as the time-series value-weighted return differences between the portfolios 5 and 1 formed based on the market capitalization values of the indexes. In the same vein, R_{WHMLt} is defined as the time-series value-weighted return differences between the portfolios 5 and 1 formed based on the earnings-to-price ratios of the indexes. Since the factors are constructed by using the total sample of the country-industry indexes, they are referred as the World *SMB* and *HML* factors. The definition of R_{Wt} is the same as in Equation (1.11).

The last model, the international FFC4 model, also adds Carhart's (1997) momentum factor on the three factors of Fama-French defined as in Equation (1.13):

$$\begin{aligned} R_{5-1t} = \alpha_{FFC4} + \beta_W R_{Wt} + \beta_{WSMB} R_{WSMBt} \\ + \beta_{WHML} R_{WHMLt} + \beta_{WWML} R_{WWMLt} + \varepsilon_t \end{aligned} \quad (1.13)$$

where R_{WWMLt}, which is referred as winner-minus-loser factor, shows the returns on the portfolios based on the momentum effect; and α_{FFC4} shows the Jensen alpha from the international version of the FFC4 model Similarly, R_{WWMLt} is defined as the time-series value-weighted return differences between the portfolios 5 and 1 formed based on the momentum variable, which is the cumulative returns on the indexes from month *t*-12 to month *t*-2. The definitions of other variables are given previously. Similarly, World *WML* is also constructed for each month using the total sample of the country-industry indexes. All these international asset-pricing models are performed by using the time-series observations for the whole sample.

The Jensen's alphas obtained from the international models are used to determine the existence of the portfolios that generate statistically significant abnormal risk-adjusted returns. This issue is tested by investigating that whether the Jensen alphas from the international asset-pricing models are statistically different than zero. The hypothesis for the Jensen's alpha is defined as

$H_0: \alpha_0 = 0$

$H_1: \alpha_0 \neq 0$

The null hypothesis refers that the risk-adjusted return difference between portfolios 5 and 1 are the same and the alternative hypothesis states the opposite. Rejecting the null hypothesis points out that the long-short portfolio earns abnormal returns, which means that the risk-adjusted returns of the extreme portfolios are statistically different. In other words, it can be concluded that the relevant index attribute has an impact on international index returns that is free from the effect of systematic risk factors.

1.4.1.2. Bivariate Portfolio Sorts

Bivariate portfolio analysis has almost the same processes with univariate analysis. Unlike univariate portfolios, in bivariate portfolio analyses, indexes are sorted based on two index attributes. In this dissertation chapter, market capitalization values of the indexes are used as the first sort variable whereas each of the remaining index attributes are used as the second sort variable. More specifically, bivariate portfolio analysis aims to investigate the cross-sectional relation between the index returns and each of the eighteen index attributes under the control of the size effect. As a result, size based bivariate portfolio analysis enable us to examine whether the significance of the index attributes are the reflections of the size effect. Although bivariate portfolio analysis is performed as independent and dependent sorts (Bali et al., 2016:52), in this dissertation chapter, I only perform dependent bivariate portfolio sorts.

As explained in the univariate portfolio analysis, the first step is the determination of the number of portfolios, which is defined as 5 in this dissertation chapter. Thereafter, all country-industry indexes are sorted based on market capitalization values and quintile portfolio are formed. Thus, indexes in each size quintile have similar market capitalization values. Then, within each size quintile, the indexes are furtherly sorted based on an index attribute and quintile portfolios are formed. These attribute based quintile portfolios in each size quintile have similar values of the relevant index attribute, but exhibit dispersion in the market capitalization values, which controls for the size effect. As a result, I generate 5x5 bivariate portfolios sorted on size and then, an index attribute. Similarly, the bivariate portfolios are formed for every month in the sample period. After portfolio formation process, equal-weighted returns of each portfolio are calculated over the next month with the indexes in the relevant portfolio. Thereafter, the time-series means of each portfolio returns are calculated over the months in the sample as shown in Equations (1.9) and (1.10).

Similar with the univariate portfolio analysis, it is investigated that whether the long-short portfolios of each index attribute provide equal-weighted raw and risk-adjusted returns within each size quintile. Firstly, a mean difference t-test is performed between the time-series average returns on extreme value portfolios for the whole research period under the control of the size effect. In addition, the cross-sectional relation between the relevant index attribute and index returns under the control of the size effect is also examined after controlling for sensitivity of the portfolios to systematic risk factors based on ICAPM, and the international versions of the FF3 and FFC4 models. These processes are explained in detail in the univariate portfolio analysis section.

1.4.2. Index-level Cross-Sectional Regression Analysis

The previous section concentrated on portfolio analysis, which investigates the cross-sectional relation between index returns and the sorted index attribute(s). It is stated that the most important advantage of portfolio analysis is being a nonparametric technique with no any assumptions about the data. However, with portfolio analysis it is difficult to examine the relation under the control of a large set of control variables (Bali e al. 2016:89). Moreover, Fama and MacBeth (1973, FM thereafter) regression analysis is developed to examine the relationship between pairs of variables by allowing under the control of a large set of other variables. On the other hand, unlike portfolio analysis, FM regression has some assumptions that needed to be met.

In this dissertation chapter, I aim to examine the relationship between future index returns and a set of variables, which are explained in the anomalies section. An index-level cross-sectional regression, whose general from is represented by Equation (1.14), are performed. This regression equation regresses one-month ahead excess return of the given index (R_{it+1}) on the index attributes of that index in month *t*. However, this equation will be revised by depending on the correlation analyses and include only the index attributes that have been found to affect index returns in the portfolio-level analyses.

$$\begin{aligned} R_{it+1} = \beta_{0t} &+ \beta_{1t}Range_{it} + \beta_{2t}MAX_{it} + \beta_{3t}MIN_{it} + \beta_{4t}SD_{it} + \beta_{5t}IVOL_{it} \\ &+ \beta_{6t}BETA_{it} + \beta_{7t}TSKEW_{it} + \beta_{8t}ISKEW_{it} + \beta_{9t}MV_{it} \\ &+ \beta_{10t}EP_{it} + \beta_{11t}DY_{it} + \beta_{12t}\,EBITDA/EV_{it} \\ &+ \beta_{13t}IntMom_{it} + \beta_{14t}StMom_{it} + \beta_{15t}OP_{it} + \beta_{16t}ES_{it} \\ &+ \beta_{17t}ROE_{it} + \beta_{18t}INV_{it} + \beta_{19t}NSI_{it} + \varepsilon_{it} \end{aligned} \tag{1.14}$$

where R_{it+1} indicates the realized return on *i*. international index in month *t*+1 and all index attributes are the ones obtained from month *t*. Lastly, ε_{it} shows the error term.

Moreover, some nested versions of the index-level cross-sectional regressions will be run every month in the whole research period.

In the second step of FM regression technique, the regression coefficients and R-squared results of the cross-sectional regressions are time-series averaged over the months in the sample. The aim of time-series averaging the regression coefficients is to examine that whether the null hypothesis stating that the time-series average of the regression coefficients is different from zero. In other words, the index attributes that have non-zero slopes are identified.

$H_0: \beta_k = 0$

$H_1: \beta_k \neq 0$

Rejecting the null hypothesis means that the cross-sectional relation between the relevant index attribute and international index returns is statistically significant in the average time period.

1.5. Results

1.5.1. Portfolio Analyses

1.5.1.1. Univariate Portfolio Sorts

Table 1.3 reports the monthly times-series means of the equal-weighted returns on quintile portfolios based on each index attribute. In addition, the time-series means of the raw return differences between portfolios 5 and 1; and the Jensen alphas obtained from the ICAPM (α_{ICAPM}) and the international versions of the FF3 (α_{FF3}) and FFC4 (α_{FFC4}) models are presented. All t-statistics are adjusted based on the methodology of Newey and West (1987).

< Table 1.3 here >

The results show that the time-series means of the equal-weighted raw return differences between the extreme value portfolios based on the index attributes of *Range*, *MAX*, *MIN*, *SD*, *IVOL*, *BETA*, *TSKEW*, *ISKEW*, *MV*, *EP*, *DY*, *EBITDA/EV*, *IntMom*, *StMom*, *ROE,* and *NSI* are significantly different from zero. In other words, these results imply that the zero-cost portfolio trading strategy based on these index attributes can generate significant raw excess returns. In addition, after adjusting the returns to the relevant risk factors, the hypothesis for the Jensen alphas obtained from the ICAPM, international FF3, and international FFC4 models being equal to zero are rejected for all the anomalies above, except for α_{FFC4} value of *ROE*. The results from the international versions of the asset-pricing models imply that the arbitrage profits based on these index attributes are still exist even after adjusting the returns to some risk factors. On the other hand, the trading strategies based on *OP*, *ES*, and *INV* provide neither raw nor risk-adjusted returns.

< Table 1.4 here >

Table 1.4 presents the value-weighted portfolio results and the corresponding Newey-West (1987) adjusted t-statistics. The raw and all risk-adjusted return differences from the long-short portfolios based on *MAX* and *MIN* are still strongly significant for all international asset-pricing models. Moreover, even though the raw and risk-adjusted return differences and t-statistic values decrease in magnitude (raw return differences from -0.0110, 0.0077 to -0.0090, 0.0055, respectively), *MV* and *IntMom* are also still significant trading strategies. In addition, *BETA* also persistently provides significant results. The results indicate that the weight of the portfolio causes change in the results of some of the index attributes. *Range*, *SD*, and *TSKEW* becomes totally insignificant whereas *IVOL*, *ISKEW*, *EP*, *DY*, *EBITDA/EV*, *StMom*, and *NSI* fail to provide both significant raw and risk-adjusted returns simultaneously. On the other hand, the effects of *OP* and *ES* become significant and generate abnormal returns for the three different benchmark models, except for α_{FFC4} value of *OP*. Furthermore, the results for *INV* and *ROE* do not change depending on the weight of the portfolio; *ROE* still provides significant trading strategies while *INV* does not.

In conclusion, the results of the equal- and value-weighted portfolios have remarkable differences. Firstly, the number of significant trading strategies decreases from equal- to value-weighted portfolios. Secondly, the significance of some index attributes changes across weights of the portfolio. Since value-weighted portfolios take into account the market capitalization values while equal-weighted portfolios do not, the differences in the results of equal- and value-weighted portfolios can be caused by the size effect. Therefore, starting from this point of view, I conduct bivariate sorts on size and other index attributes to examine the size effect on the predictive ability of the index attributes in the next subsection.

1.5.1.2. Bivariate Portfolio Sorts

This section aims to test whether some anomalies are existent or stronger only for a specific size portfolio(s). In addition, it is also aimed to clarify whether the observed anomalies based on several index attributes can be merely a reflection of a size anomaly because of the potential correlation of size with other index attributes. Table 1.5 presents the results of bivariate portfolio sorts based on size and other eighteen index attributes.

< Table 1.5 here >

The first five columns show the time-series means of equal-weighted returns on each *Range* quintile as well as the time-series means of raw and risk-adjusted return differences between the extreme *Range* portfolios within each size quintile. 5-1*MV* column shows the time-series means of the return difference between extreme size portfolios for each *Range* quintile. The time-series means of raw return differences between *Range*5 and *Range*1 for the size quintiles of *MV*1, *MV*2, and *MV*3 are strongly significant with the corresponding adjusted t-statistics of 7.22, 4.67, and 3.07, respectively. Moreover, when the returns are adjusted to some risk factors, the risk-adjusted returns for the 5-1*Range* portfolio in the smallest size quintiles of *MV*1 and *MV*2 preserve consistently their significance from all three different international asset-pricing models with the t-statistics varying from 2.29 to 8.79. However, for the size quintile of *MV*3, the risk-adjusted return on the 5-1*Range* portfolio is only statistically different from zero for the ICAPM with the t-statistic of 2.55. For the largest size quintiles of *MV*4 and *MV*5, all the raw and risk-adjusted returns on the 5-1*Range* portfolios are not statistically different from zero. As a result, it can be concluded that *Range* strongly affects returns on indexes having small market capitalization values. In Panel A of Table 1.5, the intersection cell of 5-1*MV* column and the 5-1*Range* row shows the time-series mean of the raw return difference between the 5-1*Range* portfolio for *MV*5 and that for *MV*1, which is -0.0407 with the t-statistic of -7.88, is statistically significant. The Jensen alpha values for the same return difference are also strongly significant for the tree international asset-pricing models with the t-statistics -8.36, -8.07, and -8.16, respectively. These results indicate that the positive relation between *Range* and future index returns is higher for the indexes with low values of size than for the indexes with high values of size. Moreover, these results are in line with the results of univariate portfolio analyses in Table 1.3, where *Range* generates abnormal returns for the equal-weighted portfolios that are dominated by small indexes.

Panels B and C present the results of the bivariate portfolio analyses based on size and then *MAX* and *MIN*, respectively. Both the raw and all three risk-adjusted return differences between the extreme value portfolios of *MAX* and *MIN* are strongly significant regardless of the size quintiles. Interestingly, raw and risk-adjusted returns on 5-1*MAX* (5-1*MIN*) portfolios within size quintiles decrease (increase) monotonically from *MV*1 to *MV*5, which suggests that the documented positive (negative) relation can be stronger for small-cap indexes as compared to large-cap indexes. Moreover, for both *MAX* and *MIN* the results of the last column indicate that the time-series means of the raw and risk-adjusted return differences between the 5-1*MAX* / 5-1*MIN* portfolios for the size quintiles of *MV*5 and *MV*1 are statistically significant. These results show that *MAX* and *MIN* have strong explanatory powers on future returns under the control of size and even after adjusting the returns with three different benchmark models. In addition, these findings support the results in Tables 1.3 and 1.4 indicating that the *MAX* and *MIN* effects are strongly exist regardless of the size of portfolios.

The results for the bivariate sorts on size and the traditional total volatility measure of *SD*, as well as the idiosyncratic volatility, *IVOL*, are shown in Panels D and E of Table 1.5, respectively. For the smallest three size quintiles of *MV*1, *MV*2, and *MV*3, the 5-1*SD* and 5-1*IVOL* portfolios provides significant raw returns with the corresponding strong t-statistics spreads from 3.04 to 7.98. For the small-cap indexes in *MV*1 and *MV*2, the arbitrage profits still remain persistent even after adjusting the returns to some risk factors in the three different international asset-pricing models. However, for the size quintile of *MV*3, the risk-adjusted returns survive only for the ICAPM. On the other hand, although the raw returns on 5-1*SD* and 5-1*IVOL* portfolios for the size quintile of *MV*4 are significant, the Jensen alphas fails to be significant for all benchmark models. For the largest size quintile of *MV*5, the raw and risk-adjusted return differences of 5-1*SD* and 5-1*IVOL* portfolios turn out to be insignificant. According to the last columns of these panels, it is found that the raw return differences between the 5-1*SD* / 5-1*IVOL* portfolios for the size quintiles of *MV*5 and *MV*1 strongly depart from zero with the corresponding t-statistics -8.67 and -8.37, respectively. When the return differences are adjusted to risk under three benchmark models, the Jensen alphas are still highly significant. So, these evidences are enough to conclude that similar with the previously mentioned volatility measures, both the *SD* and *IVOL* effects are more important for the returns on the small-cap country-industry portfolios. On the other hand, the results of the other volatility measure of *BETA* in Panel F yields neither significant raw nor risk-adjusted returns for all size segments.

In Panels G and H of Table 1.5, the results for the bivariate sorts on *Size-TSKEW* and *Size-ISKEW* indicate that the 5-1*TSKEW* and 5-1*ISKEW* portfolios provides significant raw returns and risk adjusted returns from three benchmark models only for the small-cap indexes in *MV*1 and *MV*2 size quintiles. The skewness effect melts away for the large-cap indexes. The last columns of these panels show that the return differences between the extreme skewness portfolios for the size quintiles of *MV*5 and *MV*1 provides at least one evidence to conclude that the relation between skewness measures and expected index returns differs across small- and large-cap indexes.

The Panels from I to K present the returns on the value measures of *EP*, *DY*, and *EBITDA/EV* portfolios within each size quintile, respectively. For the smallest three size quintiles of *MV*1, *MV*2, and *MV*3, there are significant raw returns for the extreme value portfolios. For these size quintiles, the returns are consistently significant even after adjusting to risk under three different benchmark models. For the *MV*4 size quintile, while 5-1*DY* provides consistently significant raw and risk-adjusted returns, 5-1*EP* and 5-1*EBITDA/EV* generate significant raw returns and risk-adjusted returns in some cases. Moreover, for the large-cap indexes in *MV*5, the return differences between the extreme value portfolios of *EP* and *DY* yield one for each significant results while the raw and risk-adjusted returns of 5-1*EBITDA/EV* portfolios are persistently significant. The relation between value measures and expected index returns changes across small- and large-cap indexes for different definitions of the value effect. In addition, these results suggest that the value effect exist for every size quintile depending on the definition of the value measure.

The bivariate portfolio results for the momentum effect in Panels L and M point out that the raw and risk-adjusted returns on the difference of extreme momentum portfolios are distinguished from zero in all size segments, except large-cap indexes in *MV*5. For the large-cap indexes, the momentum effect loses its explanatory power on index returns. As stated earlier, the last column shows the relation between the long-short momentum portfolios across size quintiles. The results indicate that the raw and risk-adjusted return differences between the 5-1*IntMom* and 5-1*StMom* portfolios within quintiles *MV*5 and *MV*1 depart from zero. These findings suggest that there is a strong relation between momentum measures and index returns, which is much stronger for small-cap indexes.

Next, I move on to the results for the profitability measures presented in Panels from N to P. The returns on 5-1*ES* portfolios are significantly different from zero only for the large-cap indexes in size quintile of *MV*5 while the returns on 5-1*ROE* are for the small-cap indexes in size quintiles of *MV*1 and *MV*2. For both profitability measures, the last columns also indicate that the return differences between the extreme value of the profitability measures for the size quintiles of *MV*5 and *MV*1 are distinguished from zero. On the other hand, when profitability is measured as operating profitability, it yields neither significant raw nor risk-adjusted returns for all size segments. As a result, it can be concluded that profitability effect has explanatory power on the small-cap indexes when it is measured as *ROE*; on the large-cap indexes when it is measured as *ES*.

The last two panels present the results for the stand-alone measures of *INV* and *NSI*. Similar with *BETA* and *OP*, *INV* does not generate significant raw and risk-adjusted returns for all size segments. These results are in consistent with the equal- and value-weighted univariate portfolio sorts. On the other hand, *NSI* provides significant raw and risk adjusted returns mostly for the large-cap indexes. However, the return difference between the long-short *NSI* portfolios across the largest and smallest size quintiles are statistically not distinguished from zero indicating that the relation between *NSI* and expected returns do not differs for small and large-cap indexes.

There are important inferences from the bivariate sorts. The significant trading strategies based on the volatility measures of *Range*, *SD*, and *IVOL* still exist for small-cap quintiles even after controlling for size whereas for those based on *MAX* and *MIN* strongly exist regardless of the size segments. These findings reveal that the abnormal returns earned from the trading strategies based on *MAX* and *MIN* are independent from the size effect. The results for *Range*, which is the newly proposed proxy for total volatility, generates positive abnormal returns similar with the traditional total volatility measure of *SD*. Moreover, the results of correlation analysis in Table 1.2 also shows that *Range* is highly correlated with *SD* and thereafter with *IVOL*, *MAX*, and *MIN*, respectively. As a result, starting from the definition of *Range*, which includes both maximum and minimum returns in it, *Range* combines the *MAX* and *MIN* anomalies, thus can be used as an alternative measure of total volatility.

Furthermore, *TSKEW*, *ISKEW*, *ROE* affect the returns on only small-cap portfolios while *ES* affects the ones on the large-cap portfolios. The value effect is significant for all size segments depending on its definition; *EP* and *DY* for small- and medium-cap portfolios, and *EBITDA/EV* for small- and large-cap portfolios. Moreover, the measures of momentum effect, *IntMom* and *StMom*, provide abnormal returns for both small- and medium-cap portfolios. On the other hand, the index attributes of *BETA*, *OP*, and *INV* fails to significantly affect index returns for all size segments. Lastly, there is a significant *NSI* effect, but this effect can show up among mixed portfolio sizes. The predictive abilities of some index attributes are better for the returns on small-cap indexes rather than the large-cap indexes. The reason of this difference can be explained as many of the anomalies found significant in Table 1.3 still have arbitrage opportunities waited to be exploited by the investors. Our index-level portfolio analyses are in line with those of Fama and French (2008), which indicate that there is a larger average return spreads between high and low portfolios for small-cap stocks. The implication of these results might be beneficial for portfolio managers, so that they can exploit the existing arbitrage opportunities by constructing their investment strategies for small-cap country-industry portfolios.

1.5.2. Index-level Cross-Sectional Regression Analysis

1.5.2.1. Cross-Sectional Regressions for the Full Sample

Table 1.6 presents the regression coefficients, which are time-series averaged over the months in the research period, with the corresponding Newey and West (1987) adjusted t-statistics. Because of the high correlations among the measures of volatility, size, value, momentum, and profitability effects as reported in Table 1.2, the index attributes that are in the same anomaly group are not included in the same regression specification simultaneously. Moreover, the measures of value, momentum, skewness, and profitability, *EP*, *IntMom*, *TSKEW*, and *OP* are used as the main measures and drop *DY*, *StMom*, *ISKEW*, and *ROE*, respectively, which are the alternative measures, from the main regression analyses. Later on, in robustness tests, the main variables are replaced with their alternative counterparts to investigate whether the usage of alternative measurement approaches for these variables causes changes in the results of Table 1.6.

The first five regression specifications exclude the index attributes of *EBITDA/EV*, *OP*, *ES*, *INV*, and *NSI* and the last five ones present the results for the specifications including these variables. For the first five regression specifications, the research period extends from March 1974 to July 2015. Since the construction of these control variables requires more past data, the research period for the last five ones extends from September 1985 to July 2015.

< Table 1.6 here >

The results show that all volatility measures, except *BETA*, have significant effects on future index returns with the corresponding strong t-statistics. Their strong effects are also robust to the usage of a more recent data due to the inclusion of the remaining control variables. On the other hand, the other volatility measure of *BETA* also provides some significant slope coefficients, but its significance is not consistent for all regression specifications, especially when more control variables are included. The index attributes of *EP*, *IntMom*, and *EBITDA/EV* provide significant slope estimates for all regression specifications regardless of the inclusion of the remaining index attributes and shortening the research period. Moreover, *TSKEW* and *MV* have effects on future index returns only for mixed versions of the regression specifications. On the other hand, *INV*, which is found to have insignificant explanatory power on returns according to the portfolio sorts, provides significant slope coefficients under some circumstances. Lastly, *OP*, *ES*, and *NSI* do not provide any evidence for the significant prediction of index returns, since their slopes are not different from zero in all regression specifications.

In summary, *Range*, *MAX*, *MIN*, *SD*, *IVOL*, *EP*, *IntMom*, and *EBITDA/EV* significantly affect index returns even after controlling for a large set of control variables. The next section investigates whether the results of the regression analyses in Table 1.6 change across different size quintiles as similarly analyzed by bivariate sorts in Table 1.5.

1.5.2.2. Cross-Sectional Regressions across Size Quintiles

In this section, the fundamental regression specifications in Table 1.6 are performed for size quintiles. Each panel of Table 1.7 shows the results for different size segments from *MV*1 including the small-cap indexes, Panel A, to *MV*5 including the large-cap indexes, Panel E. The results show that *Range*, *SD*, and *IVOL* have persistently significant effects on index returns of small-cap quintiles of *MV*1, *MV*2, and *MV*3, however, their regression coefficients decrease sharply from the smallest to the largest size quintile and do not survive for the size quintiles of *MV*4 and *MV*5. On the other hand, the effects of *MAX* and *MIN* as well as *IntMom* are persistently significant for portfolios of any size. These findings for volatility and momentum measures are consistent with the results of bivariate sorts in Table 1.5.

< Table 1.7 here >

Furthermore, *EP* provides almost persistently significant slope coefficients for size quintiles of *MV*2, *MV*3, *MV*4, and *MV*5 and *EBITDA/EV* for size quintiles of *MV*4. The results for *EP* and *EBITDA/EV* suggest that value anomalies based on these variables can be a reflection of the portfolios with different sizes. On the other hand, the skewness measure of *TSKEW* and profitability measure of *ES*, which are found to have significant effects on the returns of small-cap portfolios and large-cap portfolios, respectively, in bivariate portfolio sorts, nearly do not survive under the control of other index attributes. Moreover, the index attributes of *MV*, *OP*, *NSI*, and *INV* provides too few numbers of significant slope estimates in some regression specifications, but these results are not consistent across size quintiles in general. As a result, it can be concluded that the impacts of *TSKEW*, *ES*, *MV*, *OP*, *NSI*, and *INV* anomalies are not consistent across size portfolios under the control of other variables in cross-sectional regressions.

1.5.3. Robustness Tests

1.5.3.1. Alternative Regression Specifications

The previous regression analyses use the fundamental measures for the effects of value, momentum, skewness, and profitability. In this subsection, I use the alternative measures of these anomalies to investigate whether the results of these anomalies are sensitive to their definitions. More specifically, Table 1.8 presents the results of the regressions, which use alternative counterparts of *DY*, *StMom*, *ISKEW*, and *ROE* instead of *EP*, *IntMom*, *TSKEW*, and *OP*, respectively.

< Table 1.8 here >

The results for the alternative variables are mainly consistent with results of the regression specifications including the main variables in Table 1.6. More specifically, the predictive ability of all volatility measures as well as *Range*, except *BETA*, on future index returns are strongly significant. Similarly, *BETA* as well as *ISKEW* and *MV* have some significant slope estimates across different regression specifications, however still do not provide consistent results. In addition, *DY*, *StMom*, and *EBITDA/EV* have persistently significant effects on future index returns even though the inclusion of the remaining control variables shortens the research period. Lastly, the effects of the profitability measures of *ES* and *ROE*; the stand-alone measure of *NSI* are still insignificant. The results generally show that the impacts of the alternative variables are almost as the same as the main variables. In conclusion, it is suggested that the results of the regression specifications do not change depending on the alternative definitions of the anomalies.

< Table 1.9 here >

Similarly, when the regression specifications for the size quintiles in Table 1.7 are repeated with the alternative definitions of anomalies, the slope coefficients of *Range*, *SD*, and *IVOL* decrease pointedly in Table 1.9. In other words, from the smallest size quintile of *MV*1 to the largest size quintile of *MV*5 the slope estimates decrease and beyond that they lose their explanatory power for the size quintiles of *MV*4 and *MV*5. Furthermore, the high value of the explanatory power of *MAX* and *MIN* are consistently significant in regression specifications for all size quintiles. Moreover, the effects of *BETA*, *ISKEW*, and *MV* change across regression specifications and size quintiles. Although the measures of value effect do not provide consistent results and exist across mixed size quintiles, it can be shown that *DY* is mainly significant in the regression specification run with fewer number of control variables and *EBITDA/EV* is generally significant for medium-cap portfolios. In addition, the momentum effect is still powerful for small- and medium-cap indexes since the slope estimates from *StMom* are significant for the size quintiles from *MV*1 to *MV*4. The predictive ability of profitability effect is significant depending on its measures; *ES* for small-cap indexes whereas *ROE* for large-cap indexes. Lastly, the stand alone measures of *NSI* exists for the size quintiles of *MV*2 and *MV*3 while *NSI* is consistently insignificant for all size segments. The results suggest that the value, momentum, skewness, and profitability effects are again not sensitive to the alternative definitions of them across different size segments. As a result, it can be concluded that the usage of the alternative definitions of these anomalies does not cause remarkable changes in the regression results.

1.5.3.2. Bivariate Portfolio Sorts for the Total Volatility Measures

The high correlation between *Range* and *SD* do not enable us to include both of these variables in the regression specifications at the same time because of the multi-collinearity problem. Therefore, it is aimed to observe the conditional effect between *Range* and *SD* by performing bivariate portfolio analyses between each other. In this subsection, I examine the *Range* effect on index returns after controlling for *SD* and the *SD* effect on index returns after controlling for *Range*. Firstly, to control for *SD*, quintile portfolios are formed by sorting the indexes based on *SD*, and then within each *SD* quintile the indexes furtherly sorted based on *Range* and quintile portfolios are formed. The resulting *Range* portfolios in each *SD* quintile have similar values of standard deviation but exhibit dispersion in the values of *Range* and thus, enable us to control for *SD*. Next, the returns on average *SD* portfolios ($SD_{\text{ew-Avg}}$ and $SD_{\text{vw-Avg}}$) are calculated by taking the equal- and value-weighted averages of returns across all *SD* quintiles within a *Range* quintile. This operation is repeated for all five *Range* portfolios. Lastly, it is tested that whether low- and high-*Range* portfolios for the average *SD* portfolios earn significant raw or risk-adjusted returns. In Panel A of Table 1.10, the results show that the 5–1*Range* portfolio provides significant equal- and value-weighted raw returns for the average *SD* portfolio. When the returns are adjusted for risk under several factor models, only one out of the three Jensen alphas turn out to be significant. More specifically, the risk-adjusted returns survive only for the benchmark model of ICAPM and turn out to be insignificant when more risk factors are included in the models. These results show that once *SD* has been controlled for, *Range* carries not so much useful information beyond the information content of *SD*.

< Table 1.10 here >

In Panel B of Table 1.9, the roles of *Range* and *SD* are changed to determine the effect of *SD* under the control of *Range*. The results indicate that for the equal- and value-weighted average *Range* portfolios ($Range_{\text{ew-Avg}}$ and $Range_{\text{vw-Avg}}$), 5-1*SD* portfolios generate both positive significant raw and risk-adjusted returns. Moreover, when the returns on 5-1*SD* portfolios are adjusted for factor sensitivities under various benchmark models, 5-1*SD* portfolios still yield significant non-zero risk-adjusted returns. Therefore, it can be concluded that the effect of *SD* on equal- and value-weighted index returns remains strong even after controlling for *Range*.

Because equal-weighted portfolios are dominated by small indexes and value-weighted portfolios give more emphasis to indexes with high market capitalization, these results suggest that *SD* contains useful information beyond the information content of *Range* in explaining the returns of both small-cap and large-cap indexes. On the other hand, under the control of *SD*, *Range* does not add so much power to the explanation of the return on neither small- nor large-cap index portfolios beyond the explanatory power of *SD*. In conclusion, it is suggested that *SD* is a stronger determinant of index returns than *Range* for small- and large-cap indexes However, *Range* provides easier computation of total volatility and fewer data than *SD*, which still makes *Range* more practical to use.

1.6. Conclusion

In this chapter, I examined the cross-sectional relationship between nineteen index attributes and expected index returns for country-industry indexes with 19 industries from 37 countries. I focused on several anomalies, specifically measures of volatility, skewness, momentum, profitability, size and value effects, and some stand-alone measures. In addition, the volatility measures also included the newly proposed term *Range*, defined as the difference between the maximum and minimum daily returns over the past month, and offered as an alternative measure of total volatility. Firstly, univariate portfolio-level analyses were performed to examine whether the quintile portfolios formed based on nineteen index attributes provide significant differences between the raw returns and risk-adjusted returns of extreme value portfolios. Moreover, since some anomalies can merely reflect a size anomaly, I performed bivariate portfolio sorts based on size and other eighteen index attributes to investigate the behavior of the anomalies after controlling for size. In addition to the portfolio-level analyses, I also examined the cross-section of index returns through index-level cross-sectional regression analyses, which allow the effects of several index attributes to be controlled for simultaneously. The index-level cross-sectional regressions were also performed for each size quintile to examine the significance of the index attributes across different size quintiles of country-industry indexes. Lastly, I examined the conditional relationship between the total volatility measures of *Range* and *SD* by performing bivariate portfolio analyses each other.

The results showed that *Range*, which includes both maximum and minimum returns, is highly correlated with other volatility measures and has a strongly significant effect on index returns. It can thus be used as an alternative measure of total volatility. In addition, *Range* is easier to calculate and requires less data, which makes it a more practical measure of total volatility than the traditional measure of standard deviation. Moreover, the univariate and size-based bivariate portfolios show that the volatility measures of *Range*, standard deviation, and idiosyncratic volatility only affect the returns on small-cap indexes whereas *MAX* and *MIN* have strong effects in all size quintiles, although most strongly for small-cap indexes. These findings suggest that the abnormal returns earned from trading strategies based on volatility measures are not driven by the size effect. The results also indicate that there are value and momentum effects across a wide range of portfolio sizes depending on the definition of the value and momentum measures. The effects of the skewness measures show up exclusively in small-cap portfolios while the profitability measure of *ROE* is concentrated in small size quintiles and *ES* especially in large-cap portfolios. On the other hand, the index attributes of *BETA*, *OP*, and *INV* do not have significant effects on index returns for any size segment. Lastly, *NSI* significantly affected index returns, but only for mixed size portfolios.

The index-level cross-sectional regression results show significant effects of volatility, momentum, and value anomalies, even after controlling for a large set of control variables. Moreover, the size-based regression analyses indicate that the effects of *Range*, *SD*, and *IVOL* are significant for small and medium-cap indexes whereas *MAX* and *MIN* have significant effects across all sizes. Moreover, the predictive power of value and momentum effects are significant for almost all size segments. Replacing the fundamental definitions of the value, momentum skewness, and profitability effects with the alternative ones in the regression equations did not change the results. In other words, the index-level cross-sectional regression results are robust to the use of alternative definitions of these anomalies after controlling for other variables.

I also evaluated the two total volatility measures of the return range and standard deviation. Since neither could be included in the same regression specifications because they were highly correlated, I examined the marginal effect of one in the presence of the other by performing bivariate sorts between them. The results show that range loses its predictive ability after controlling for the standard deviation for both equal- and value-weighted portfolios, whereas the standard deviation still explains the returns of equal- and value-weighted portfolios after controlling for range. This suggests that the standard deviation contains much more information than range in explaining the average returns of both small- and large-cap indexes. However, because it is easier to compute and requires less data, *Range* is still a more practical measure of total volatility than standard deviation.

The results presented in this chapter have several beneficial implications for international portfolio management. Firstly, examining the effects of the index level counterparts of recently documented and traditional stock level return predictors helps those aiming to diversify their portfolios across country-industry indexes. Secondly, the behavior of some index attributes reflects the size effect in that their predictive abilities varies across different sizes, particularly for small-cap indexes. This implies that there are various total volatility, idiosyncratic volatility, momentum, and value anomalies provide arbitrage opportunities for small-cap indexes that active portfolio managers could exploit.

1.7. Tables

Table 1.1. Basic Statistics

This table provides the basic statistics for the nineteen index attributes. First, the cross-sectional mean of each index attribute is calculated across 19 supersector indexes of 37 markets every month in the whole sample period. Then, the cross-sectional means are time-series averaged over the months. The standard deviation, maximum, and minimum values are computed using the monthly time-series data. *Range* is the difference between the previous month's maximum and minimum daily returns; *MAX* is the maximum daily index return within a month; *MIN* is the negative of the minimum daily index return within a month; *SD* represents the standard deviation of daily returns within a month; *IVOL* represents the idiosyncratic volatility; *BETA* represents the market beta; *TSKEW* stands for the total skewness; *ISKEW* stands for the idiosyncratic skewness; *MV* shows the market value in $US billions, *EP* shows the earnings-to-price ratio, *DY* shows the dividend yield, *EBITDA/EV* shows the earnings before interest, taxes, depreciation, and amortization over enterprise value; *IntMom* stands for the intermediate-term momentum; *StMom* stands for the short-term momentum; *OP* shows the operating profitability; *ES* shows the earnings surprise; *ROE* shows the return on equity; *INV* represents the investments; and *NSI* represents the net share issuance. The research period is January 1973-July 2015. Start date changes across local supersectors.

Factors	*Mean*	*Std. Dev.*	*Max*	*Min*
Range	0.0011	0.0049	0.0959	0.0001
MAX	0.0006	0.0031	0.0637	0.0001
MIN	0.0005	0.0019	0.0322	0.0001
SD	0.0012	0.0049	0.0941	0.0002
IVOL	0.0011	0.0045	0.0850	0.0001
BETA	0.0084	0.0403	0.8811	-0.0120
TSKEW	0.0017	0.0173	0.3522	-0.0324
ISKEW	0.0019	0.0137	0.2737	-0.0339
MV	86.0643	84.6638	1439.1220	16.9869
EP	0.0010	0.0027	0.0466	0.0002
DY	0.0004	0.0013	0.0222	0.0001
EBITDA/EV	0.0048	0.0110	0.1320	0.0002
IntMom	0.0004	0.0008	0.0030	-0.0049
StMom	0.0002	0.0008	0.0072	-0.0041
OP	0.0040	0.0154	0.2489	-0.0014
ES	0.0189	0.1288	1.3011	-0.0008
ROE	0.2637	0.7662	10.3689	0.0077
INV	0.0051	0.0090	0.1123	0.0002
NSI	0.0010	0.0033	0.0544	0.0000

Table 1.2. Correlation Matrix

For the sample of country-industry indexes, correlation analyses between the nineteen index attributes are conducted from January 1973 to July 2015. The correlation analyses performed with two steps. In the first step, every month in the sample period the cross-correlations among the index attributes across the indexes are calculated. Then, the cross-correlations are time-series averaged over the months in the research period.

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.8849	1																	
MIN	0.8521	0.5242	1																
SD	0.9594	0.8519	0.8159	1															
IVOL	0.9139	0.8158	0.7738	0.9466	1														
BETA	0.3202	0.2741	0.2889	0.3564	0.1212	1													
TSKEW	0.0852	0.0867	0.0613	0.0863	0.0857	0.0089	1												
ISKEW	0.0678	0.0692	0.0478	0.0686	0.0633	0.0192	0.9064	1											
MV	-0.2515	-0.2309	-0.2093	-0.2466	-0.3291	0.1923	-0.0745	-0.0461	1										
EP	0.0419	0.0382	0.0406	0.0399	0.0557	-0.0375	-0.0406	-0.0568	-0.1224	1									
DY	-0.0518	-0.0507	-0.0380	-0.0635	-0.0385	-0.0874	-0.1212	-0.1453	-0.0815	0.4119	1								
EBITDA /EV	0.0517	0.0454	0.0461	0.0555	0.0645	-0.0073	-0.0115	-0.0177	-0.1014	0.2461	0.1179	1							
IntMom	0.0200	0.0203	0.0110	0.0241	0.0286	0.0068	0.1236	0.1621	0.0023	-0.1040	-0.1451	-0.0144	1						
StMom	0.0007	0.0047	-0.0061	0.0026	0.0089	-0.0054	0.1274	0.1535	0.0091	-0.1156	-0.1312	0.0129	0.6171	1					
OP	-0.0055	-0.0072	-0.0027	-0.0074	-0.0012	-0.0185	0.0049	0.0040	0.0302	0.0811	0.0890	0.0663	0.0105	0.0114	1				
ES	0.0044	-0.0016	0.0083	0.0111	0.0054	0.0235	0.0119	0.0211	0.0248	-0.0259	-0.0312	-0.0010	0.0914	0.0773	-0.0153	1			
ROE	-0.0114	-0.0134	-0.0065	-0.0151	-0.0040	-0.0331	-0.0144	-0.0053	0.0015	0.1465	0.0921	0.0941	0.0999	0.0531	0.3968	-0.0063	1		
INV	0.0208	0.0184	0.0203	0.0212	0.0271	-0.0038	0.0203	0.0125	-0.0298	-0.0006	-0.0254	-0.0327	-0.0064	-0.0110	0.0323	-0.0113	0.0094	1	
NSI	0.0210	0.0151	0.0208	0.0225	0.0301	-0.0099	-0.0068	-0.0071	-0.0538	0.0095	-0.0351	-0.0406	0.0296	0.0003	-0.0227	-0.0076	-0.0244	0.0425	1

Table 1.3. Returns on Equal-Weighted Portfolios Sorted by Several Attributes

For the sample of country-industry indexes, the quintile portfolios are formed for every month from January 1973 to July 2015 by sorting the indexes based on nineteen index attributes over the past one month. Portfolio 1 (5) includes the indexes with the lowest (highest) values of a sort variable. The equal-weighted returns on the quintile portfolios and the 5-1 long-short portfolios are calculated over the next month. The 5-1 portfolio is the zero-cost arbitrage portfolio, which longs the portfolio with the highest variable and shorts the one with the lowest variable. Average raw return differences and Jensen alphas from the international versions of the ICAPM, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4) for the 5-1 portfolio are presented in the last four columns, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Portfolio Returns								
	1	2	3	4	5	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
Range	0.0079	0.0097	0.0113	0.0135	0.0256	0.0177***	0.0143***	0.0062***	0.0064***
						(5.12)	(5.48)	(3.25)	(3.20)
MAX	-0.0133	0.0004	0.0092	0.0187	0.0533	0.0666***	0.0635***	0.0563***	0.0566***
						(19.17)	(25.28)	(29.12)	(23.76)
MIN	0.0334	0.0217	0.0150	0.0079	-0.0103	-0.0437***	-0.0464***	-0.0524***	-0.0521***
						(-15.43)	(-21.06)	(-28.93)	(-27.97)
SD	0.0075	0.0093	0.0107	0.0131	0.0275	0.0200***	0.0162***	0.0078***	0.0081***
						(5.43)	(5.96)	(3.84)	(3.81)
IVOL	0.0072	0.0091	0.0103	0.0132	0.0282	0.0209***	0.0178***	0.0087***	0.0091***
						(5.94)	(6.51)	(4.59)	(4.57)
BETA	0.0189	0.0118	0.0112	0.0112	0.0149	-0.0040**	-0.0071***	-0.0065***	-0.0066***
						(-1.72)	(-3.75)	(-3.48)	(-3.41)
TSKEW	0.0132	0.0124	0.0128	0.0144	0.0172	0.0040***	0.0036***	0.0029**	0.0028**
						(3.39)	(3.03)	(2.34)	(2.18)
ISKEW	0.0132	0.0124	0.0128	0.0138	0.0179	0.0047***	0.0045***	0.0041***	0.0038***
						(4.16)	(3.97)	(3.60)	(3.23)
MV	0.0206	0.0145	0.0120	0.0114	0.0096	-0.0110***	-0.0115***	-0.0102***	-0.0104***
						(-6.66)	(-7.41)	(-6.88)	(-7.04)
EP	0.0104	0.0116	0.0117	0.0138	0.0175	0.0070***	0.0071***	0.0049***	0.0052***
						(3.92)	(4.03)	(3.11)	(3.57)
DY	0.0113	0.0113	0.0119	0.0136	0.0173	0.0060***	0.0064***	0.0049***	0.0056***
						(3.44)	(3.71)	(3.53)	(4.37)
EBITDA/EV	0.0121	0.0118	0.0127	0.0145	0.0192	0.0071***	0.0072***	0.0055***	0.0052***
						(5.13)	(5.09)	(4.13)	(3.79)
IntMom	0.0118	0.0113	0.0127	0.0135	0.0195	0.0077***	0.0086***	0.0094***	0.0094***
						(2.87)	(3.36)	(3.61)	(3.61)
StMom	0.0121	0.0101	0.0111	0.0132	0.0194	0.0073***	0.0083***	0.0085***	0.0049**
						(2.91)	(3.41)	(3.57)	(2.51)
OP	0.0150	0.0133	0.0129	0.0141	0.0143	-0.0007	-0.0007	0.0002	0.0000
						(-0.51)	(-0.53)	(0.17)	(0.02)
ES	0.0109	0.0128	0.0114	0.0119	0.0113	0.0004	0.0007	0.0010	0.0001
						(0.31)	(0.56)	(0.69)	(0.11)
ROE	0.0130	0.0125	0.0141	0.0148	0.0162	0.0033**	0.0036**	0.0031**	0.0021
						(2.09)	(2.29)	(2.02)	(1.44)
INV	0.0154	0.0130	0.0132	0.0133	0.0129	-0.0025	-0.0029*	-0.0024	-0.0022
						(-1.42)	(-1.81)	(-1.47)	(-1.28)
NSI	0.0155	0.0139	0.0135	0.0123	0.0137	-0.0018*	-0.0024**	-0.0025***	-0.0027***
						(-1.65)	(-2.41)	(-2.60)	(-2.85)

Table 1.4. Returns on Value-Weighted Portfolios Sorted by Several Attributes

For the sample of country-industry indexes, the quintile portfolios are formed for every month from January 1973 to July 2015 by sorting the indexes based on nineteen index attributes over the past one month. Portfolio 1 (5) includes the indexes with the lowest (highest) values of a sort variable. The value-weighted returns on the quintile portfolios and the 5-1 long-short portfolios are calculated over the next month. The 5-1 portfolio is the zero-cost arbitrage portfolio, which longs the portfolio with the highest variable and shorts the one with the lowest variable. Average raw return differences and Jensen alphas from the international versions of the ICAPM, the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4) for the 5-1 portfolio are presented in the last four columns, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Portfolio Returns								
	1	2	3	4	5	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
Range	0.0091	0.0095	0.0097	0.0098	0.0136	0.0045	0.0004	-0.0029	-0.0024
						(1.10)	(0.12)	(-1.06)	(-0.81)
MAX	-0.0043	0.0072	0.0143	0.0206	0.0385	0.0428***	0.0392***	0.0370***	0.0374***
						(10.92)	(12.62)	(13.12)	(12.70)
MIN	0.0234	0.0126	0.0062	-0.0033	-0.0214	-0.0447***	-0.0476***	-0.0502***	-0.0499***
						(-15.28)	(-20.51)	(-21.78)	(-21.39)
SD	0.0089	0.0098	0.0096	0.0098	0.0154	0.0065	0.0021	-0.0015	-0.0012
						(1.50)	(0.64)	(-0.50)	(-0.39)
IVOL	0.0090	0.0088	0.0086	0.0132	0.0167	0.0077*	0.0048	-0.0017	-0.0019
						(1.91)	(1.40)	(-0.56)	(-0.61)
BETA	0.0134	0.0105	0.0092	0.0079	0.0083	-0.0051**	-0.0083***	-0.0054***	-0.0053**
						(-2.08)	(-3.74)	(-2.56)	(-2.42)
TSKEW	0.0103	0.0096	0.0099	0.0089	0.0096	-0.0007	-0.0017	0.0007	0.0014
						(-0.36)	(-0.87)	(0.36)	(0.75)
ISKEW	0.0094	0.0090	0.0088	0.0091	0.0122	0.0028	0.0020	0.0051***	0.0052***
						(1.52)	(1.06)	(2.85)	(2.90)
MV	0.0176	0.0141	0.0120	0.0117	0.0086	-0.0090***	-0.0093***	-0.0073***	-0.0074***
						(-4.96)	(-5.23)	(-4.82)	(-4.85)
EP	0.0069	0.0096	0.0101	0.0111	0.0122	0.0054**	0.0057**	0.0007	0.0015
						(2.23)	(2.33)	(0.29)	(0.64)
DY	0.0081	0.0092	0.0101	0.0112	0.0119	0.0039*	0.0050**	0.0005	0.0009
						(1.69)	(2.23)	(0.46)	(0.74)
EBITDA/EV	0.0083	0.0104	0.0111	0.0124	0.0122	0.0039**	0.0046**	0.0011	0.0003
						(2.12)	(2.53)	(0.71)	(0.20)
IntMom	0.0070	0.0079	0.0109	0.0115	0.0125	0.0055*	0.0063**	0.0075***	0.0075***
						(1.87)	(2.21)	(2.62)	(2.62)
StMom	0.0084	0.0074	0.0080	0.0099	0.0132	0.0048*	0.0059**	0.0058*	0.0008
						(1.69)	(2.12)	(1.94)	(0.34)
OP	0.0078	0.0084	0.0100	0.0117	0.0110	0.0031*	0.0036*	0.0029*	0.0022
						(1.70)	(1.92)	(1.66)	(1.36)
ES	0.0085	0.0088	0.0102	0.0102	0.0043	-0.0042**	-0.0040**	-0.0043**	-0.0051***
						(-2.30)	(-2.12)	(-2.13)	(-2.71)
ROE	0.0069	0.0097	0.0105	0.0119	0.0115	0.0047**	0.0058**	0.0047**	0.0031*
						(1.99)	(2.54)	(2.42)	(1.74)
INV	0.0108	0.0107	0.0098	0.0091	0.0101	-0.0007	-0.0019	0.0003	0.0001
						(-0.39)	(-0.99)	(0.15)	(0.07)
NSI	0.0100	0.0102	0.0095	0.0088	0.0087	-0.0014	-0.0024	-0.0032*	-0.0037**
						(-0.82)	(-1.56)	(-1.86)	(-2.09)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute

The size quintiles are formed for every month in the research period by sorting the country-industry indexes based on *MV* and each of other index attribute. The indexes are firstly sorted based on *MV* and size quintiles are formed. Then, the indexes in each size quintile are further sorted based on an index attribute, so that twenty-five portfolios are obtained. Each column in the table except the last one reports the equal-weighted average monthly returns on the indexes that are sorted by an index attribute after controlling for size. The last column, 5-1*MV*, indicates the return difference between high-cap and low-cap indexes. 5-1 portfolio in each size quintile longs the portfolio with the highest values of an index attribute and shorts the one with the lowest values. Second sort variables of index attribute changes in each panel from A to S. Average raw return differences and Jensen alphas from the international versions of the ICAPM, the Fama-French three-factor model (FF3), and Fama-French-Carhart four-factor model (FFC4) on 5-1 portfolio in each size quintile are presented in the last four rows, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Bivariate sorts on *MV* and *Range*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *Range*	0.0069	0.0076	0.0077	0.0075	0.0093	0.0024
2	0.0087	0.0116	0.0113	0.0098	0.0095	0.0008
3	0.0153	0.0129	0.0112	0.0117	0.0086	-0.0067
4	0.0220	0.0146	0.0099	0.0144	0.0106	-0.0114
5 High *Range*	0.0495	0.0253	0.0190	0.0130	0.0112	-0.0383
5-1 *Range*	0.0426***	0.0177***	0.0113***	0.0055	0.0018	-0.0407***
	(7.22)	(4.67)	(3.07)	(1.57)	(0.64)	(-7.88)
α_{CAPM} (5-1)	0.0384***	0.0141***	0.0080**	0.0017	-0.0016	-0.0401***
	(8.79)	(4.50)	(2.55)	(0.62)	(-0.74)	(-8.36)
α_{FF3} (5-1)	0.0264***	0.0062**	0.0016	-0.0034	-0.0021	-0.0367***
	(8.00)	(2.29)	(0.56)	(-1.29)	(-0.95)	(-8.07)
α_{FFC4} (5-1)	0.0260***	0.0068**	0.0025	-0.0036	-0.0024	-0.0367***
	(7.94)	(2.44)	(0.86)	(-1.33)	(-1.06)	(-8.16)

Panel B: Bivariate sorts on *MV* and *MAX*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *MAX*	-0.0214	-0.0152	-0.0138	-0.0106	-0.0068	0.0146
2	-0.0076	-0.0022	0.0009	0.0016	0.0021	0.0097
3	0.0098	0.0081	0.0090	0.0099	0.0087	-0.0011
4	0.0302	0.0221	0.0177	0.0187	0.0161	-0.0140
5 High *MAX*	0.0897	0.0583	0.0442	0.0361	0.0284	-0.0613
5-1 *MAX*	0.1111***	0.0735***	0.0579***	0.0467***	0.0352***	-0.0759***
	(19.76)	(19.01)	(15.92)	(13.46)	(11.16)	(-16.86)
α_{CAPM} (5-1)	0.1076***	0.0704***	0.0549***	0.0434***	0.0320***	-0.0756***
	(25.71)	(23.13)	(18.37)	(15.73)	(12.98)	(-17.56)
α_{FF3} (5-1)	0.0960***	0.0626***	0.0494***	0.0389***	0.0317***	-0.0726***
	(30.19)	(21.98)	(18.09)	(14.89)	(13.11)	(-17.81)
α_{FFC4} (5-1)	0.0960***	0.0630***	0.0506***	0.0391***	0.0315***	-0.0729***
	(30.14)	(20.07)	(17.65)	(14.04)	(12.33)	(-17.86)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel C: Bivariate sorts on *MV* and *MIN*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *MIN*	0.0463	0.0365	0.0326	0.0300	0.0269	-0.0195
2	0.0319	0.0264	0.0231	0.0191	0.0183	-0.0136
3	0.0242	0.0172	0.0153	0.0134	0.0103	-0.0139
4	0.0131	0.0072	0.0036	0.0070	0.0047	-0.0085
5 High *MIN*	-0.0111	-0.0134	-0.0142	-0.0127	-0.0104	0.0007
5-1 *MIN*	-0.0575***	-0.0498***	-0.0468***	-0.0427***	-0.0373***	0.0202***
	(-11.88)	(-15.86)	(-15.49)	(-13.49)	(-15.19)	(4.38)
α_{CAPM} (5-1)	-0.0605***	-0.0527***	-0.0494***	-0.0457***	-0.0400***	0.0205***
	(-15.31)	(-19.19)	(-18.14)	(-17.71)	(-20.45)	(4.82)
α_{FF3} (5-1)	-0.0678***	-0.0580***	-0.0536***	-0.0496***	-0.0404***	0.0225***
	(-20.60)	(-22.78)	(-20.97)	(-20.38)	(-20.30)	(5.33)
α_{FFC4} (5-1)	-0.0679***	-0.0578***	-0.0532***	-0.0494***	-0.0405***	0.0223***
	(-20.73)	(-22.10)	(-20.14)	(-19.68)	(-19.85)	(5.20)

Panel D: Bivariate sorts on *MV* and *SD*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *SD*	0.0063	0.0068	0.0073	0.0075	0.0093	0.0029
2	0.0077	0.0100	0.0105	0.0092	0.0090	0.0013
3	0.0120	0.0118	0.0110	0.0116	0.0088	-0.0032
4	0.0207	0.0159	0.0112	0.0144	0.0106	-0.0102
5 High *SD*	0.0554	0.0275	0.0191	0.0137	0.0115	-0.0439
5-1 *SD*	0.0491***	0.0207***	0.0117***	0.0062*	0.0022	-0.0469***
	(7.91)	(5.30)	(3.04)	(1.69)	(0.71)	(-8.67)
α_{CAPM} (5-1)	0.0445***	0.0168***	0.0081**	0.0023	-0.0016	-0.0461***
	(10.02)	(5.31)	(2.50)	(0.76)	(-0.70)	(-9.45)
α_{FF3} (5-1)	0.0312***	0.0084***	0.0012	-0.0037	-0.0023	-0.0426***
	(9.31)	(3.11)	(0.43)	(-1.35)	(-1.03)	(-9.13)
α_{FFC4} (5-1)	0.0311***	0.0091***	0.0022	-0.0039	-0.0029	-0.0432***
	(9.28)	(3.23)	(0.75)	(-1.41)	(-1.25)	(-9.33)

Panel E: Bivariate sorts on *MV* and *IVOL*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *IVOL*	0.0059	0.0066	0.0071	0.0071	0.0085	0.0026
2	0.0080	0.0105	0.0098	0.0092	0.0091	0.0011
3	0.0109	0.0113	0.0106	0.0118	0.0089	-0.0021
4	0.0211	0.0153	0.0121	0.0139	0.0100	-0.0111
5 High *IVOL*	0.0556	0.0282	0.0197	0.0145	0.0126	-0.0431
5-1 *IVOL*	0.0498***	0.0215***	0.0126***	0.0074**	0.0041	-0.0457***
	(7.98)	(5.65)	(3.36)	(2.10)	(1.48)	(-8.37)
α_{CAPM} (5-1)	0.0452***	0.0179***	0.0094***	0.0040	0.0016	-0.0436***
	(10.22)	(5.73)	(2.94)	(1.38)	(0.72)	(-9.17)
α_{FF3} (5-1)	0.0319***	0.0098***	0.0027	-0.0016	-0.0007	-0.0407***
	(9.50)	(3.70)	(0.93)	(-0.58)	(-0.33)	(-8.57)
α_{FFC4} (5-1)	0.0317***	0.0104***	0.0036	-0.0016	-0.0014	-0.0413***
	(9.48)	(3.81)	(1.21)	(-0.57)	(-0.61)	(-8.70)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel F: Bivariate sorts on *MV* and *BETA*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *BETA*	0.0320	0.0206	0.0173	0.0117	0.0117	-0.0203
2	0.0144	0.0116	0.0117	0.0104	0.0095	-0.0049
3	0.0125	0.0114	0.0103	0.0106	0.0095	-0.0030
4	0.0155	0.0116	0.0096	0.0116	0.0093	-0.0062
5 High *BETA*	0.0286	0.0172	0.0109	0.0122	0.0091	-0.0194
5-1 *BETA*	-0.0034	-0.0034	-0.0064	0.0005	-0.0025	0.0009
	(-0.76)	(-1.13)	(-2.29)	(0.19)	(-0.93)	(0.18)
α_{CAPM} (5-1)	-0.0057	-0.0061	-0.0090	-0.0026	-0.0062	-0.0004
	(-1.41)	(-2.15)	(-3.50)	(-1.13)	(-2.77)	(-0.09)
α_{FF3} (5-1)	-0.0061	-0.0075	-0.0104	-0.0047	-0.0037	0.0034
	(-1.73)	(-2.71)	(-4.06)	(-1.99)	(-1.70)	(0.77)
α_{FFC4} (5-1)	-0.0068	-0.0079	-0.0097	-0.0052	-0.0033	0.0044
	(-1.96)	(-2.73)	(-3.57)	(-2.20)	(-1.48)	(1.03)

Panel G: Bivariate sorts on *MV* and *TSKEW*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *TSKEW*	0.0177	0.0131	0.0130	0.0117	0.0097	-0.0080
2	0.0193	0.0133	0.0100	0.0126	0.0104	-0.0089
3	0.0224	0.0137	0.0117	0.0121	0.0108	-0.0117
4	0.0207	0.0153	0.0125	0.0099	0.0096	-0.0111
5 High *TSKEW*	0.0239	0.0184	0.0145	0.0124	0.0106	-0.0133
5-1 *TSKEW*	0.0062^{**}	0.0053^{***}	0.0015	0.0008	0.0009	-0.0053
	(2.28)	(2.93)	(0.77)	(0.44)	(0.54)	(-1.62)
α_{CAPM} (5-1)	0.0065^{**}	0.0050^{***}	0.0012	0.0001	0.0001	-0.0064^{**}
	(2.42)	(2.72)	(0.60)	(0.08)	(0.03)	(-1.96)
α_{FF3} (5-1)	0.0048^{*}	0.0049^{***}	0.0008	0.0005	0.0027	-0.0045
	(1.85)	(2.65)	(0.34)	(0.24)	(1.53)	(-1.40)
α_{FFC4} (5-1)	0.0044^{*}	0.0049^{**}	0.0008	0.0006	0.0029	-0.0039
	(1.67)	(2.53)	(0.37)	(0.27)	(1.62)	(-1.15)

Panel H: Bivariate sorts on *MV* and *ISKEW*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *ISKEW*	0.0173	0.0130	0.0133	0.0111	0.0098	-0.0075
2	0.0224	0.0128	0.0113	0.0129	0.0094	-0.0130
3	0.0192	0.0144	0.0107	0.0113	0.0105	-0.0087
4	0.0208	0.0158	0.0114	0.0115	0.0106	-0.0102
5 High *ISKEW*	0.0244	0.0179	0.0150	0.0119	0.0109	-0.0135
5-1 *ISKEW*	0.0071^{***}	0.0049^{***}	0.0017	0.0008	0.0011	-0.0060^{**}
	(2.63)	(2.69)	(0.87)	(0.53)	(0.65)	(-1.99)
α_{CAPM} (5-1)	0.0070^{***}	0.0047^{**}	0.0015	0.0005	0.0007	-0.0064^{**}
	(2.69)	(2.53)	(0.74)	(0.27)	(0.37)	(-1.98)
α_{FF3} (5-1)	0.0052^{**}	0.0048^{**}	0.0012	0.0008	0.0036^{**}	-0.0043
	(2.08)	(2.55)	(0.57)	(0.47)	(2.04)	(-1.38)
α_{FFC4} (5-1)	0.0047^{*}	0.0044^{**}	0.0011	0.0007	0.0034^{**}	-0.0039
	(1.88)	(2.31)	(0.50)	(0.41)	(1.87)	(-1.22)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel I: Bivariate sorts on *MV* and *EP*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *EP*	0.0180	0.0108	0.0065	0.0091	0.0065	-0.0115
2	0.0154	0.0128	0.0104	0.0106	0.0099	-0.0055
3	0.0156	0.0138	0.0107	0.0117	0.0099	-0.0057
4	0.0179	0.0146	0.0135	0.0116	0.0108	-0.0071
5 High *EP*	0.0260	0.0173	0.0161	0.0128	0.0113	-0.0147
5-1 *EP*	0.0080^{**}	0.0065^{***}	0.0096^{***}	0.0037^{*}	0.0048^{**}	-0.0033
	(2.00)	(2.95)	(4.68)	(1.81)	(1.96)	(-0.74)
α_{CAPM} (5-1)	0.0084^{**}	0.0062^{***}	0.0095^{***}	0.0033^{*}	0.0052^{**}	-0.0032
	(2.27)	(2.92)	(4.67)	(1.68)	(2.12)	(-0.75)
α_{FF3} (5-1)	0.0079^{**}	0.0058^{***}	0.0091^{***}	0.0023	0.0006	-0.0078^{**}
	(2.55)	(2.83)	(4.38)	(1.15)	(0.24)	(-1.97)
α_{FFC4} (5-1)	0.0075^{**}	0.0055^{***}	0.0094^{***}	0.0032^{*}	0.0010	-0.0081^{**}
	(2.50)	(2.80)	(4.84)	(1.68)	(0.40)	(-2.10)
Panel J: Bivariate sorts on *MV* and *DY*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *DY*	0.0167	0.0124	0.0086	0.0105	0.0077	-0.0090
2	0.0154	0.0127	0.0107	0.0095	0.0093	-0.0061
3	0.0177	0.0124	0.0125	0.0098	0.0090	-0.0087
4	0.0203	0.0126	0.0136	0.0111	0.0103	-0.0099
5 High *DY*	0.0254	0.0183	0.0138	0.0147	0.0117	-0.0137
5-1 *DY*	0.0088^{***}	0.0060^{**}	0.0053^{**}	0.0042^{**}	0.0041^{*}	-0.0047
	(2.99)	(2.26)	(2.52)	(2.16)	(1.69)	(-1.40)
α_{CAPM} (5-1)	0.0086^{***}	0.0065^{***}	0.0057^{***}	0.0042^{**}	0.0049^{**}	-0.0037
	(2.99)	(2.60)	(2.69)	(2.20)	(2.14)	(-1.10)
α_{FF3} (5-1)	0.0084^{***}	0.0064^{***}	0.0060^{***}	0.0041^{**}	0.0008	-0.0077^{***}
	(3.02)	(2.61)	(2.95)	(2.32)	(0.59)	(-2.57)
α_{FFC4} (5-1)	0.0089^{***}	0.0067^{***}	0.0078^{***}	0.0052^{***}	0.0013	-0.0083^{***}
	(3.27)	(2.94)	(4.01)	(3.02)	(0.93)	(-2.68)
Panel K: Bivariate sorts on *MV* and *EBITDA/EV*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *EBITDA/EV*	0.0158	0.0110	0.0104	0.0102	0.0071	-0.0091
2	0.0139	0.0124	0.0095	0.0098	0.0094	-0.0047
3	0.0177	0.0136	0.0120	0.0103	0.0101	-0.0079
4	0.0186	0.0148	0.0122	0.0124	0.0107	-0.0083
5 High *EBITDA/EV*	0.0292	0.0189	0.0153	0.0135	0.0121	-0.0171
5-1 *EBITDA/EV*	0.0131^{***}	0.0079^{***}	0.0049^{***}	0.0033^{*}	0.0051^{***}	-0.0080^{*}
	(3.11)	(3.73)	(2.86)	(1.76)	(2.81)	(-1.73)
α_{CAPM} (5-1)	0.0127^{***}	0.0073^{***}	0.0049^{***}	0.0035^{*}	0.0062^{***}	-0.0065
	(3.26)	(3.50)	(2.58)	(1.79)	(3.53)	(-1.49)
α_{FF3} (5-1)	0.0110^{***}	0.0065^{***}	0.0053^{**}	0.0024	0.0043^{**}	-0.0083^{*}
	(3.46)	(3.23)	(2.52)	(1.14)	(2.52)	(-1.88)
α_{FFC4} (5-1)	0.0102^{***}	0.0061^{***}	0.0053^{**}	0.0024	0.0037^{**}	-0.0081^{*}
	(3.23)	(3.01)	(2.51)	(1.11)	(2.09)	(-1.87)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel L: Bivariate sorts on *MV* and *IntMom*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *IntMom*	0.0190	0.0117	0.0104	0.0079	0.0081	-0.0109
2	0.0143	0.0111	0.0108	0.0111	0.0093	-0.0050
3	0.0203	0.0137	0.0110	0.0112	0.0101	-0.0102
4	0.0183	0.0149	0.0125	0.0123	0.0121	-0.0062
5 High *IntMom*	0.0301	0.0209	0.0157	0.0154	0.0114	-0.0187
5-1 *IntMom*	0.0111***	0.0092**	0.0053*	0.0075***	0.0033	-0.0078**
	(2.67)	(2.50)	(1.71)	(2.77)	(1.23)	(-2.16)
α_{CAPM} (5-1)	0.0122***	0.0106***	0.0062**	0.0085***	0.0040	-0.0082**
	(3.16)	(3.05)	(1.99)	(3.23)	(1.48)	(-2.08)
α_{FF3} (5-1)	0.0136***	0.0108***	0.0066**	0.0094***	0.0034	-0.0077**
	(3.53)	(3.14)	(2.00)	(3.30)	(1.27)	(-2.08)
α_{FFC4} (5-1)	0.0136***	0.0108***	0.0066**	0.0094***	0.0034	-0.0098**
	(3.53)	(3.14)	(2.00)	(3.30)	(1.27)	(-2.55)
Panel M: Bivariate sorts on *MV* and *StMom*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *StMom*	0.0180	0.0106	0.0118	0.0086	0.0092	-0.0087
2	0.0130	0.0101	0.0107	0.0102	0.0088	-0.0042
3	0.0147	0.0130	0.0094	0.0106	0.0092	-0.0055
4	0.0207	0.0150	0.0111	0.0114	0.0103	-0.0104
5 High *StMom*	0.0310	0.0220	0.0144	0.0147	0.0112	-0.0198
5-1 *StMom*	0.0130***	0.0113***	0.0026	0.0061**	0.0019	-0.0111***
	(3.22)	(3.33)	(0.97)	(2.45)	(0.77)	(-3.03)
α_{CAPM} (5-1)	0.0141***	0.0126***	0.0036	0.0072***	0.0029	-0.0113***
	(3.65)	(3.79)	(1.29)	(2.98)	(1.17)	(-3.08)
α_{FF3} (5-1)	0.0139***	0.0122***	0.0037	0.0080***	0.0029	-0.0110***
	(3.78)	(3.80)	(1.27)	(3.02)	(1.12)	(-2.96)
α_{FFC4} (5-1)	0.0113***	0.0087***	-0.0002	0.0046**	-0.0013	-0.0127***
	(3.24)	(2.88)	(-0.08)	(1.99)	(-0.63)	(-3.21)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel N: Bivariate sorts on *MV* and *OP*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *OP*	0.0211	0.0134	0.0132	0.0124	0.0083	-0.0128
2	0.0199	0.0150	0.0123	0.0117	0.0086	-0.0113
3	0.0203	0.0136	0.0130	0.0131	0.0097	-0.0106
4	0.0172	0.0148	0.0116	0.0132	0.0129	-0.0043
5 High *OP*	0.0214	0.0147	0.0125	0.0135	0.0108	-0.0105
5-1 *OP*	0.0002	0.0013	-0.0007	0.0012	0.0025	0.0023
	(0.06)	(0.63)	(-0.37)	(0.72)	(1.35)	(0.47)
α_{CAPM} (5-1)	0.0003	0.0012	-0.0003	0.0013	0.0025	0.0022
	(0.08)	(0.61)	(-0.17)	(0.83)	(1.29)	(0.51)
α_{FF3} (5-1)	0.0016	0.0008	-0.0001	0.0012	0.0010	0.0012
	(0.52)	(0.41)	(-0.06)	(0.80)	(0.56)	(0.28)
α_{FFC4} (5-1)	0.0016	0.0008	-0.0003	0.0008	0.0004	0.0005
	(0.52)	(0.39)	(-0.17)	(0.54)	(0.24)	(0.13)

Panel O: Bivariate sorts on *MV* and *ES*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *ES*	0.0123	0.0112	0.0110	0.0094	0.0092	-0.0032
2	0.0164	0.0122	0.0113	0.0132	0.0084	-0.0080
3	0.0174	0.0118	0.0118	0.0110	0.0092	-0.0082
4	0.0144	0.0112	0.0125	0.0110	0.0106	-0.0038
5 High *ES*	0.0156	0.0143	0.0099	0.0108	0.0040	-0.0115
5-1 *ES*	0.0032	0.0031	-0.0011	0.0014	-0.0052***	-0.0084**
	(1.08)	(1.28)	(-0.52)	(0.86)	(-2.73)	(-2.49)
α_{CAPM} (5-1)	0.0039	0.0033	-0.0008	0.0021	-0.0050**	-0.0089***
	(1.34)	(1.40)	(-0.36)	(1.27)	(-2.48)	(-2.63)
α_{FF3} (5-1)	0.0034	0.0028	0.0007	0.0022	-0.0058***	-0.0087**
	(1.12)	(0.97)	(0.31)	(1.30)	(-2.68)	(-2.45)
α_{FFC4} (5-1)	0.0027	0.0016	-0.0001	0.0014	-0.0065***	-0.0089**
	(0.91)	(0.60)	(-0.05)	(0.85)	(-3.09)	(-2.41)

Panel P: Bivariate sorts on *MV* and *ROE*

Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *ROE*	0.0166	0.0117	0.0112	0.0104	0.0081	-0.0085
2	0.0168	0.0141	0.0108	0.0107	0.0090	-0.0078
3	0.0189	0.0129	0.0141	0.0121	0.0105	-0.0084
4	0.0232	0.0144	0.0119	0.0120	0.0115	-0.0117
5 High *ROE*	0.0269	0.0158	0.0124	0.0118	0.0109	-0.0160
5-1 *ROE*	0.0103***	0.0041*	0.0012	0.0013	0.0028	-0.0075**
	(3.18)	(1.71)	(0.60)	(0.66)	(1.23)	(-2.16)
α_{CAPM} (5-1)	0.0105***	0.0049**	0.0018	0.0016	0.0033	-0.0073**
	(3.63)	(2.14)	(0.90)	(0.77)	(1.54)	(-2.16)
α_{FF3} (5-1)	0.0103***	0.0042*	0.0015	0.0011	0.0013	-0.0096***
	(3.48)	(1.70)	(0.75)	(0.55)	(0.73)	(-2.92)
α_{FFC4} (5-1)	0.0094***	0.0032	0.0007	0.0002	0.0002	-0.0099***
	(3.27)	(1.36)	(0.35)	(0.09)	(0.10)	(-3.03)

Table 1.5. Returns on Portfolios from Bivariate Sorts on Size and an Index Attribute (cont.)

Panel R: Bivariate sorts on *MV* and *INV*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *INV*	0.0228	0.0143	0.0147	0.0122	0.0099	-0.0129
2	0.0191	0.0145	0.0128	0.0123	0.0095	-0.0096
3	0.0193	0.0155	0.0126	0.0117	0.0094	-0.0099
4	0.0186	0.0146	0.0113	0.0124	0.0098	-0.0088
5 High *INV*	0.0161	0.0128	0.0113	0.0126	0.0101	-0.0060
5-1 *INV*	-0.0067	-0.0016	-0.0034	0.0005	0.0003	0.0070
	(-1.34)	(-0.66)	(-1.59)	(0.29)	(0.13)	(1.39)
α_{CAPM} (5-1)	-0.0065	-0.0021	-0.0032	0.0003	-0.0015	0.0050
	(-1.54)	(-0.90)	(-1.59)	(0.19)	(-0.76)	(1.10)
α_{FF3} (5-1)	-0.0040	-0.0030	-0.0037*	0.0005	-0.0002	0.0046
	(-1.23)	(-1.15)	(-1.65)	(0.26)	(-0.10)	(1.01)
α_{FFC4} (5-1)	-0.0035	-0.0024	-0.0035	0.0004	-0.0001	0.0041
	(-1.06)	(-0.91)	(-1.53)	(0.20)	(-0.03)	(0.94)

Panel S: Bivariate sorts on *MV* and *NSI*						
Quintiles	1 Low *MV*	2	3	4	5 High *MV*	5-1 *MV*
1 Low *NSI*	0.0245	0.0133	0.0131	0.0125	0.0110	-0.0135
2	0.0187	0.0138	0.0122	0.0122	0.0104	-0.0083
3	0.0165	0.0171	0.0118	0.0115	0.0110	-0.0054
4	0.0212	0.0142	0.0126	0.0113	0.0095	-0.0117
5 High *NSI*	0.0216	0.0146	0.0105	0.0106	0.0090	-0.0126
5-1 *NSI*	-0.0029	0.0014	-0.0026*	-0.0019	-0.0020	0.0009
	(-0.75)	(0.84)	(-1.71)	(-1.47)	(-1.47)	(0.23)
α_{CAPM} (5-1)	-0.0040	0.0013	-0.0033**	-0.0025*	-0.0026**	0.0014
	(-1.15)	(0.80)	(-2.21)	(-1.86)	(-2.06)	(0.38)
α_{FF3} (5-1)	-0.0054*	0.0010	-0.0035**	-0.0022	-0.0036**	0.0010
	(-1.91)	(0.55)	(-2.38)	(-1.62)	(-2.51)	(0.28)
α_{FFC4} (5-1)	-0.0053***	0.0009	-0.0032**	-0.0026*	-0.0038***	0.0007
	(-1.91)	(0.53)	(-2.20)	(-1.86)	(-2.61)	(0.20)

Table 1.6. Cross-Sectional Regressions for the Local Industry Indexes

For each month from January 1973 to July 2015, the return of each country-industry index is regressed on the previous month's differences between maximum and minimum daily returns within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return within a month (*MAX*), the negative of the minimum daily return within a month (*MIN*), the market beta (*BETA*), the total skewness (*TSKEW*), the natural logarithm of the market capitalization (*MV*), the earnings-to-price ratio (*EP*), the intermediate-term momentum (*IntMom*), the earnings before interest, taxes, depreciation, and amortization over enterprise value (*EBITDA/EV*), the operating profitability (*OP*), the earnings surprise (*ES*), the investments (*INV*), and the net share issuance (*NSI*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *OP*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. The time-series averages of the slope coefficients and R-square values are reported in the table. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA/EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1854***					-0.0026**	-0.0007*	-0.0002	0.0401***	0.0089***						0.1557
(6.75)					(-2.39)	(-1.67)	(-0.86)	(4.42)	(4.24)						
	1.1466***				-0.0104***	-0.0018***	0.0026***	0.0296***	0.0085***						0.2281
	(25.16)				(-8.01)	(-4.69)	(8.91)	(3.31)	(3.70)						
		-0.9459***			0.0065***	0.0004	-0.0040***	0.0551***	0.0090***						0.1921
		(-21.57)			(5.81)	(0.92)	(-14.87)	(6.09)	(3.43)						
			0.2506***		-0.0034***	-0.0007**	0.0001	0.0378***	0.0090***						0.1656
			(7.87)		(-3.16)	(-1.96)	(0.43)	(4.26)	(4.45)						
				0.2454***	-0.0023**	-0.0007*	0.0002	0.0378***	0.0089***						0.1653
				(7.88)	(-1.96)	(-1.84)	(0.60)	(4.29)	(4.42)						
0.1137***					-0.0022	0.0004	-0.0001	0.0468***	0.0104***	0.0134***	-0.0011	0.3310	-0.0016*	-0.0017	0.2213
(3.22)					(-1.52)	(0.63)	(-0.33)	(3.02)	(3.34)	(3.32)	(-0.50)	(0.18)	(-1.71)	(-0.79)	
	1.1881***				-0.0133***	-0.0011*	0.0026***	0.0525***	0.0106***	0.0098**	-0.0022	1.0916	-0.0018*	-0.0015	0.2797
	(20.69)				(-7.58)	(-1.71)	(7.81)	(3.72)	(3.15)	(2.41)	(-1.13)	(0.47)	(-1.83)	(-0.63)	
		-1.1566***			0.0092***	0.0014**	-0.0034***	0.0422**	0.0089***	0.0176***	0.0005	0.9447	-0.0006	-0.0012	0.2687
		(-17.85)			(6.20)	(2.43)	(-9.53)	(2.50)	(3.07)	(4.17)	(0.21)	(0.60)	(-0.68)	(-0.52)	
			0.1495***		-0.0024	0.0002	0.0001	0.0458***	0.0107***	0.0127***	-0.0009	0.3360	-0.0016*	-0.0018	0.2279
			(3.70)		(-1.55)	(0.33)	(0.37)	(3.30)	(3.52)	(3.20)	(-0.46)	(0.18)	(-1.93)	(-0.84)	
				0.1517***	-0.0023	0.0002	0.0002	0.0453***	0.0107***	0.0127***	-0.0009	0.5454	-0.0017*	-0.0016	0.2274
				(3.91)	(-1.36)	(0.34)	(0.51)	(3.23)	(3.52)	(3.19)	(-0.48)	(0.29)	(-1.90)	(-0.73)	

Table 1.7. Cross-Sectional Regressions for Size Quintiles

For each month from January 1973 to July 2015, one-month-ahead return of each country-industry index in a size quintile is regressed on the contemporaneous values of the return range within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return within a month (*MAX*), the negative of the minimum daily return within a month (*MIN*), the market beta (*BETA*), the total skewness (*TSKEW*), the natural logarithm of the market capitalization (*MV*), the earnings-to-price ratio (*EP*), the intermediate-term momentum (*IntMom*), the earnings before interest, taxes, depreciation, and amortization over enterprise value (*EBITDA/EV*), the operating profitability (*OP*), the earnings surprise (*ES*), the investments (*INV*), and the net share issuance (*NSI*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *OP*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. Panels A, B, C, D, and E report the time-series averages of the slope coefficients and R-square values for size quintiles from *MV*1 to *MV*5. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Low *MV*1

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA/EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.2378***					0.0008	-0.0022**	-0.0031	0.0122	0.0150***						0.2767
(7.66)					(0.41)	(-2.16)	(-1.23)	(0.60)	(4.01)						
	1.1570***				-0.0057***	-0.0025***	0.0006	-0.0037	0.0136***						0.3509
	(19.60)				(-3.23)	(-2.84)	(0.21)	(-0.19)	(3.46)						
		-0.8103***			0.0070***	-0.0016	-0.0095***	0.0378**	0.0122***						0.2996
		(-13.93)			(3.87)	(-1.45)	(-4.17)	(1.93)	(3.19)						
			0.3214***		-0.0002	-0.0022**	-0.0026	0.0080	0.0151***						0.2896
			(8.97)		(-0.09)	(-2.24)	(-1.03)	(0.40)	(4.20)						
				0.3235***	0.0006	-0.0022**	-0.0025	0.0081	0.0151***						0.2897
				(9.05)	(0.30)	(-2.21)	(-1.01)	(0.39)	(4.20)						
0.2440***					0.0001	-0.0020	-0.0025	0.0211	0.0116**	0.0202	0.0093	-0.0551	0.0027	0.0064	0.4657
(3.96)					(0.02)	(-0.99)	(-0.84)	(0.60)	(2.36)	(1.03)	(1.08)	(-0.07)	(0.47)	(0.85)	
	1.4470***				-0.0133***	-0.0046***	0.0062**	0.0139	0.0128***	0.0154	-0.0041	0.1858	0.0011	0.0032	0.5212
	(15.72)				(-5.90)	(-2.73)	(2.35)	(0.36)	(2.61)	(0.87)	(-0.41)	(0.29)	(0.21)	(0.48)	
		-1.0747***			0.0120***	-0.0007	-0.0145***	0.0289	0.0082	0.0167	0.0177**	-1.0473	0.0034	0.0062	0.4908
		(-11.07)			(4.02)	(-0.30)	(-4.45)	(0.97)	(1.50)	(0.87)	(1.98)	(-1.37)	(0.63)	(0.97)	
			0.3346***		-0.0028	-0.0017	-0.0008	0.0150	0.0135***	0.0239	0.0089	-0.4052	0.0035	0.0062	0.4726
			(5.15)		(-1.02)	(-0.87)	(-0.28)	(0.43)	(2.77)	(1.33)	(1.04)	(-0.55)	(0.62)	(0.83)	
				0.3325***	-0.0018	-0.0018	-0.0009	0.0136	0.0128***	0.0228	0.0088	-0.3884	0.0039	0.0065	0.4733
				(5.16)	(-0.71)	(-0.91)	(-0.32)	(0.39)	(2.62)	(1.26)	(1.01)	(-0.53)	(0.68)	(0.87)	

Table 1.7. Cross-Sectional Regressions for Size Quintiles (cont.)

Panel B: *MV*2

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1822***					-0.0021	0.0011	-0.0007	0.0524***	0.0105***						0.2465
(5.62)					(-1.42)	(1.18)	(-0.51)	(4.43)	(3.65)						
	1.2729***				-0.0106***	-0.0008	0.0035***	0.0413***	0.0117***						0.3099
	(25.73)				(-6.28)	(-0.91)	(2.58)	(3.44)	(4.12)						
		-1.0583***			0.0074***	0.0022**	-0.0060***	0.0586***	0.0103***						0.2852
		(-21.22)			(5.07)	(2.31)	(-4.26)	(4.62)	(3.06)						
			0.2382***		-0.0030**	0.0010	-0.0003	0.0480***	0.0104***						0.2539
			(6.83)		(-1.99)	(1.13)	(-0.22)	(4.01)	(3.69)						
				0.2317***	-0.0020	0.0010	-0.0003	0.0485***	0.0104***						0.2537
				(6.70)	(-1.33)	(1.11)	(-0.25)	(4.05)	(3.71)						
0.1326**					-0.0044*	-0.0011	-0.0013	0.0146	0.0181***	0.0206*	-0.0032	-1.5800	0.0052**	-0.0096	0.3821
(1.97)					(-1.77)	(-0.94)	(-0.35)	(0.60)	(2.95)	(1.95)	(-0.58)	(-0.27)	(1.96)	(-1.64)	
	1.2784***				-0.0148***	-0.0026**	0.0036	0.0188	0.0178***	0.0054	-0.0121***	-10.5804	0.0019	-0.0067	0.4304
	(16.78)				(-6.16)	(-2.38)	(0.99)	(0.73)	(3.52)	(0.44)	(-2.93)	(-1.30)	(0.71)	(-1.20)	
		-1.1725***			0.0096***	-0.0010	-0.0081**	-0.0185	0.0200*	0.0406***	0.0012	-10.4557	0.0076**	-0.0093	0.4166
		(-13.35)			(2.97)	(-0.71)	(-2.52)	(-0.70)	(1.85)	(3.56)	(0.20)	(-1.00)	(2.37)	(-1.23)	
			0.1683**		-0.0048**	-0.0012	-0.0014	0.0146	0.0187***	0.0162*	-0.0045	-3.5173	0.0047*	-0.0107*	0.3867
			(2.49)		(-1.96)	(-1.06)	(-0.35)	(0.60)	(2.93)	(1.66)	(-0.90)	(-0.54)	(1.88)	(-1.88)	
				0.1631***	-0.0042*	-0.0010	-0.0017	0.0198	0.0173***	0.0148	-0.0049	-1.7572	0.0040*	-0.0100*	0.3866
				(2.46)	(-1.73)	(-0.91)	(-0.43)	(0.80)	(3.33)	(1.48)	(-1.02)	(-0.36)	(1.73)	(-1.81)	

Table 1.7. Cross-Sectional Regressions for Size Quintiles (cont.)

Panel C: *MV*3

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1561***					-0.0037***	-0.0006	0.0008	0.0617***	0.0129***						0.2623
(3.95)					(-2.76)	(-0.69)	(0.69)	(4.39)	(4.72)						
	1.2559***				-0.0133***	-0.0018***	0.0032***	0.0489***	0.0132***						0.3163
	(18.98)				(-7.27)	(-2.59)	(3.07)	(3.46)	(4.15)						
		-1.1167***			0.0062***	0.0006	-0.0027**	0.0735***	0.0117***						0.2929
		(-17.31)			(4.61)	(0.76)	(-2.24)	(5.34)	(3.92)						
			0.2055***		-0.0044***	-0.0007	0.0008	0.0598***	0.0138***						0.2708
			(4.74)		(-3.24)	(-0.95)	(0.72)	(4.29)	(5.01)						
				0.1982***	-0.0041***	-0.0008	0.0007	0.0591***	0.0136***						0.2703
				(4.65)	(-2.97)	(-0.96)	(0.68)	(4.25)	(5.04)						
0.1238**					-0.0038**	0.0014	-0.0018	0.0520**	0.0068*	0.0069	0.0014	0.5427	-0.0016	0.0046	0.3501
(2.33)					(-2.10)	(1.29)	(-1.12)	(2.28)	(1.77)	(0.69)	(0.41)	(0.49)	(-1.25)	(0.98)	
	1.2034***				-0.0146***	-0.0005	0.0010	0.0358	0.0085**	0.0062	-0.0066*	-1.2940	-0.0029	-0.0044	0.3916
	(14.70)				(-5.82)	(-0.46)	(0.63)	(1.36)	(2.19)	(0.59)	(-1.79)	(-0.55)	(-1.42)	(-0.76)	
		-1.1338***			0.0070***	0.0028**	-0.0046***	0.0606***	0.0079*	0.0195**	0.0073*	2.8064*	-0.0008	0.0112***	0.3858
		(-12.59)			(3.56)	(2.54)	(-3.34)	(3.25)	(1.89)	(1.94)	(1.94)	(1.71)	(-0.70)	(2.65)	
			0.1580***		-0.0045***	0.0013	-0.0013	0.0513**	0.0071*	0.0053	0.0005	-0.1254	-0.0018	0.0057	0.3535
			(2.82)		(-2.58)	(1.25)	(-0.82)	(2.14)	(1.94)	(0.53)	(0.14)	(-0.11)	(-1.40)	(1.09)	
				0.1588***	-0.0051***	0.0013	-0.0012	0.0524**	0.0071**	0.0055	0.0003	-0.0771	-0.0017	0.0059	0.3530
				(2.91)	(-2.82)	(1.27)	(-0.78)	(2.18)	(1.96)	(0.55)	(0.08)	(-0.07)	(-1.33)	(1.13)	

Table 1.7. Cross-Sectional Regressions for Size Quintiles (cont.)

Panel D: *MV*4

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1186**					-0.0001	-0.0024**	-0.0001	0.0369***	0.0112***						0.2794
(2.53)					(-0.04)	(-2.43)	(-0.06)	(3.12)	(3.94)						
	1.2176***				-0.0108***	-0.0044***	0.0014	0.0401***	0.0113***						0.3169
	(15.81)				(-6.39)	(-4.01)	(1.28)	(3.31)	(3.44)						
		-1.0756***			0.0104***	-0.0005	-0.0013	0.0373***	0.0119***						0.3105
		(-15.42)			(6.12)	(-0.48)	(-1.44)	(2.98)	(3.89)						
			0.1438***		-0.0004	-0.0023**	-0.0001	0.0375***	0.0111***						0.2848
			(2.92)		(-0.23)	(-2.35)	(-0.08)	(3.21)	(3.89)						
				0.1427***	-0.0004	-0.0023**	0.0000	0.0375***	0.0110***						0.2843
				(3.08)	(-0.28)	(-2.36)	(-0.01)	(3.21)	(3.89)						
0.0353					-0.0032*	0.0000	-0.0002	0.0412*	0.0101***	0.0157**	0.0013	0.0757	0.0002	0.0007	0.3268
(0.84)					(-1.79)	(0.01)	(-0.20)	(1.83)	(2.60)	(2.29)	(0.30)	(0.05)	(0.14)	(0.20)	
	1.1992***				-0.0168***	-0.0020**	0.0015	0.0217	0.0100*	0.0150**	-0.0044	0.4190	-0.0004	0.0019	0.3660
	(17.93)				(-7.34)	(-2.43)	(1.25)	(1.01)	(2.44)	(2.18)	(-1.08)	(0.24)	(-0.25)	(0.57)	
		-1.3342***			0.0108***	0.0016	-0.0021*	0.0470**	0.0096*	0.0176**	0.0092**	-1.0312	0.0013	-0.0013	0.3725
		(-19.59)			(5.60)	(1.55)	(-1.87)	(2.15)	(2.31)	(2.53)	(2.19)	(-0.75)	(0.80)	(-0.31)	
			0.0313		-0.0022	-0.0001	-0.0002	0.0398*	0.0102***	0.0159**	0.0014	0.0316	-0.0001	0.0003	0.3321
			(0.66)		(-1.16)	(-0.06)	(-0.22)	(1.77)	(2.70)	(2.28)	(0.33)	(0.02)	(-0.06)	(0.09)	
				0.0323	-0.0034*	-0.0001	-0.0004	0.0404*	0.0102***	0.0159**	0.0012	0.0066	0.0000	0.0004	0.3314
				(0.72)	(-1.94)	(-0.10)	(-0.33)	(1.76)	(2.68)	(2.26)	(0.28)	(0.00)	(0.01)	(0.10)	

Table 1.7. Cross-Sectional Regressions for Size Quintiles (cont.)

Panel E: High *MV*5

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA/EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.0392					0.0010	0.0000	-0.0006	0.0443**	0.0097***						0.3468
(0.96)					(0.58)	(0.04)	(-1.20)	(2.06)	(2.80)						
	1.2428***				-0.0115***	-0.0027**	0.0022***	0.0741***	0.0092***						0.3813
	(17.73)				(-6.83)	(-2.45)	(4.09)	(3.55)	(2.57)						
		-1.4574***			0.0127***	0.0022**	-0.0044***	0.0030	0.0123***						0.3855
		(-24.20)			(6.98)	(2.03)	(-8.18)	(0.13)	(3.53)						
			0.0799*		0.0005	0.0001	-0.0003	0.0489**	0.0094***						0.3522
			(1.70)		(0.26)	(0.06)	(-0.49)	(2.38)	(2.71)						
				0.0817*	-0.0004	0.0001	-0.0002	0.0488**	0.0095***						0.3521
				(1.91)	(-0.23)	(0.12)	(-0.36)	(2.39)	(2.75)						
-0.0055					-0.0008	0.0017	-0.0005	0.0997**	0.0106**	0.0016	0.0056	1.6619	-0.0005	-0.0185**	0.4187
(-0.09)					(-0.32)	(1.44)	(-0.79)	(2.36)	(2.45)	(0.23)	(1.38)	(0.46)	(-0.20)	(-2.17)	
	1.3761***				-0.0159***	-0.0010	0.0019***	0.1218***	0.0113**	0.0026	0.0029	1.1715	-0.0007	-0.0145*	0.4531
	(15.27)				(-7.19)	(-0.84)	(3.54)	(3.58)	(2.41)	(0.38)	(0.80)	(0.30)	(-0.32)	(-1.91)	
		-1.6139***			0.0151***	0.0039***	-0.0033***	0.0509	0.0140***	0.0056	0.0071*	-0.0268	-0.0005	-0.0151*	0.4617
		(-23.79)			(6.57)	(3.00)	(-5.53)	(1.28)	(3.37)	(0.83)	(1.79)	(-0.01)	(-0.21)	(-1.69)	
			0.0040		-0.0007	0.0013	-0.0005	0.0976***	0.0098**	0.0015	0.0073	1.9010	-0.0001	-0.0188**	0.4227
			(0.05)		(-0.26)	(1.32)	(-0.82)	(2.65)	(2.34)	(0.22)	(1.57)	(0.53)	(-0.06)	(-2.49)	
				0.0169	-0.0018	0.0012	-0.0004	0.0945***	0.0096**	0.0010	0.0073	1.4426	-0.0002	-0.0191**	0.4223
				(0.26)	(-0.76)	(1.25)	(-0.75)	(2.58)	(2.30)	(0.14)	(1.58)	(0.38)	(-0.07)	(-2.53)	

Table 1.8. Alternative Cross-Sectional Regressions for the Local Industry Indexes

For each month from January 1973 to July 2015, the return of each country-industry index is regressed on the previous month's differences between maximum and minimum daily returns within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return within a month (*MAX*), the negative of the minimum daily return within a month (*MIN*), the market beta (*BETA*), the idiosyncratic skewness (*ISKEW*), the natural logarithm of the market capitalization (*MV*), the dividend yield (*DY*), short-term momentum (*StMom*), the earnings before interest, taxes, depreciation, and amortization over enterprise value (*EBITDA/EV*), the earnings surprise (*ES*), the return on equity (*ROE*), the investments (*INV*), and the net share issuance (*NSI*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *ROE*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. The time-series averages of the slope coefficients and R-square values are reported in the table. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA/EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1782***					-0.0023**	0.0001	-0.0001	0.1097***	0.0147***						0.1548
(6.61)					(-2.15)	(0.23)	(-0.48)	(4.71)	(4.86)						
	1.1718***				-0.0103***	-0.0007**	0.0028***	0.1311***	0.0141***						0.2279
	(27.05)				(-7.84)	(-2.34)	(13.18)	(5.86)	(4.64)						
		-0.9992***			0.0068***	0.0008**	-0.0039***	0.0954***	0.0153***						0.1945
		(-28.96)			(6.29)	(2.55)	(-14.33)	(4.05)	(4.06)						
			0.2429***		-0.0031***	0.0000	0.0002	0.1159***	0.0148***						0.1644
			(7.86)		(-3.01)	(0.06)	(1.10)	(5.02)	(5.09)						
				0.2386***	-0.0020*	0.0000	0.0003	0.1159***	0.0148***						0.1640
				(7.86)	(-1.76)	(0.16)	(1.31)	(5.04)	(5.05)						
0.0979***					-0.0018	0.0004	-0.0003	0.0852***	0.0157***	0.0120***	-1.5246	0.0000	-0.0011*	-0.0001	0.2172
(2.75)					(-1.15)	(0.87)	(-0.98)	(3.50)	(3.73)	(3.48)	(-0.90)	(1.35)	(-1.81)	(-0.07)	
	1.2081***				-0.0136***	-0.0004	0.0025***	0.1376***	0.0176***	0.0072*	0.0744	0.0001**	-0.0010*	0.0000	0.2776
	(20.86)				(-8.38)	(-0.70)	(7.81)	(5.28)	(3.69)	(1.93)	(0.04)	(2.11)	(-1.68)	(-0.01)	
		-1.2221***			0.0096***	0.0010*	-0.0035***	0.0292	0.0122***	0.0170***	-0.8076	0.0000	-0.0012	0.0005	0.2675
		(-20.15)			(6.18)	(1.93)	(-10.19)	(1.16)	(3.11)	(4.67)	(-0.56)	(1.21)	(-1.52)	(0.26)	
			0.1273***		-0.0020	0.0003	-0.0001	0.0894***	0.0165***	0.0115***	-1.4442	0.0000	-0.0014**	0.0000	0.2236
			(2.93)		(-1.14)	(0.55)	(-0.34)	(3.65)	(3.96)	(3.38)	(-0.81)	(1.24)	(-2.01)	(0.00)	
				0.1325***	-0.0021	0.0003	-0.0001	0.0887***	0.0163***	0.0113***	-1.0632	0.0000	-0.0014	0.0002	0.2234
				(3.27)	(-1.23)	(0.53)	(-0.25)	(3.57)	(3.93)	(3.35)	(-0.58)	(1.33)	(-1.97)	(0.09)	

Table 1.9. Alternative Cross-Sectional Regressions for Size Quintiles

For each month from January 1973 to July 2015, one-month-ahead return of each country-industry index in a size quintile is regressed on the contemporaneous values of the return range within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return within a month (*MAX*), the negative of the minimum daily return within a month (*MIN*), the market beta (*BETA*), the idiosyncratic skewness (*ISKEW*), the natural logarithm of the market capitalization (*MV*), the dividend yield (*DY*), short-term momentum (*StMom*), the earnings before interest, taxes, depreciation, and amortization over enterprise value (*EBITDA/EV*), the earnings surprise (*ES*), the return on equity (*ROE*), the investments (*INV*), and the net share issuance (*NSI*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *ROE*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. Panels A, B, C, D, and E report the time-series averages of the slope coefficients and R-square values for size quintiles from *MV*1 to *MV*5. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Low *MV*1

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.2424***					0.0016	0.0000	-0.0008	0.1067**	0.0211***						0.2550
(7.72)					(0.89)	(-0.03)	(-0.74)	(2.55)	(4.75)						
	1.2531***				-0.0060***	-0.0004	0.0025**	0.1066***	0.0210***						0.3386
	(26.63)				(-3.25)	(-0.74)	(2.47)	(2.67)	(4.68)						
		-0.8958***			0.0079***	0.0004	-0.0062***	0.1306***	0.0192***						0.2817
		(-20.82)			(4.47)	(0.76)	(-5.39)	(2.91)	(3.73)						
			0.3336***		0.0002	0.0000	-0.0003	0.1159***	0.0210***						0.2689
			(9.21)		(0.11)	(0.03)	(-0.30)	(2.86)	(4.98)						
				0.3353***	0.0011	0.0000	-0.0003	0.1168***	0.0210***						0.2691
				(9.25)	(0.61)	(0.08)	(-0.30)	(2.89)	(4.95)						
0.2206***					-0.0013	-0.0024	-0.0030	0.0071	0.0098	0.0202	-1.9131*	0.0004	0.0027	0.0152	0.4590
(3.82)					(-0.39)	(-0.90)	(-0.79)	(0.07)	(0.78)	(1.09)	(-1.70)	(1.15)	(0.58)	(1.22)	
	1.3850***				-0.0146***	-0.0035	0.0080**	0.1117	0.0216**	0.0246	-0.3291	-0.0001	0.0013	0.0140	0.5160
	(13.83)				(-5.49)	(-1.47)	(2.09)	(1.61)	(2.18)	(1.71)	(-0.32)	(-0.48)	(0.26)	(1.11)	
		-1.0974***			0.0110***	-0.0011	-0.0156***	-0.0726	-0.0065	0.0086	-2.7258**	0.0008	0.0046	0.0175	0.4824
		(-10.94)			(3.60)	(-0.37)	(-3.08)	(-0.53)	(-0.34)	(0.42)	(-2.30)	(1.27)	(0.89)	(1.24)	
			0.2937***		-0.0033	-0.0020	-0.0018	-0.0099	0.0090	0.0212	-2.0257*	0.0006	0.0029	0.0161	0.4691
			(4.39)		(-0.90)	(-0.74)	(-0.44)	(-0.09)	(0.58)	(1.09)	(-1.73)	(1.15)	(0.59)	(1.21)	
				0.2950***	-0.0019	-0.0019	-0.0014	-0.0055	0.0100	0.0220	-1.9953*	0.0006	0.0031	0.0162	0.4697
				(4.51)	(-0.56)	(-0.71)	(-0.34)	(-0.05)	(0.68)	(1.14)	(-1.73)	(1.17)	(0.63)	(1.20)	

Table 1.9. Alternative Cross-Sectional Regressions for Size Quintiles (cont.)

Panel B: *MV*2

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1924***					-0.0019	0.0009	0.0002	0.0715**	0.0184***						0.2345
(5.88)					(-1.29)	(1.43)	(0.13)	(2.12)	(4.38)						
	1.3079***				-0.0103***	-0.0003	0.0046***	0.0917***	0.0177***						0.3009
	(26.57)				(-6.46)	(-0.51)	(3.66)	(2.86)	(4.04)						
		-1.0487***			0.0072***	0.0015**	-0.0057***	0.0696**	0.0189***						0.2737
		(-22.62)			(4.58)	(2.33)	(-4.34)	(2.13)	(4.10)						
			0.2491***		-0.0028*	0.0009	0.0006	0.0714**	0.0180***						0.2427
			(6.95)		(-1.85)	(1.37)	(0.52)	(2.13)	(4.26)						
				0.2416***	-0.0017	0.0009	0.0006	0.0712**	0.0181***						0.2424
				(6.81)	(-1.15)	(1.37)	(0.47)	(2.14)	(4.29)						
0.1524***					-0.0027	-0.0021	-0.0019	0.0584	0.0240***	0.0207**	-1.2749	0.0001	0.0058**	0.0000	0.3726
(3.05)					(-1.16)	(-1.47)	(-0.79)	(0.99)	(3.39)	(2.07)	(-0.39)	(1.38)	(2.00)	(-0.01)	
	1.2889***				-0.0134***	-0.0018*	0.0037**	0.0725	0.0211***	0.0182*	0.7415	0.0000	0.0028	0.0010	0.4218
	(18.17)				(-6.07)	(-1.87)	(2.15)	(1.35)	(4.02)	(1.78)	(0.21)	(-0.26)	(1.31)	(0.21)	
		-1.1778***			0.0086***	-0.0022	-0.0095***	0.0482	0.0178***	0.0303*)**	-2.4816	0.0002**	0.0063**	0.0020	0.4109
		(-16.25)			(3.08)	(-1.34)	(-3.42)	(0.81)	(2.36)	(3.22)	(-0.60)	(2.08)	(2.26)	(0.30)	
			0.1665***		-0.0029	-0.0016	-0.0031	0.0644	0.0236***	0.0167*	0.8974	0.0001	0.0051**	-0.0023	0.3778
			(2.80)		(-1.25)	(-1.42)	(-1.24)	(1.13)	(4.08)	(1.71)	(0.39)	(1.36)	(2.18)	(-0.42)	
				0.1666***	-0.0027	-0.0015	-0.0031	0.0546	0.0236***	0.0165*	1.1142	0.0001	0.0050**	-0.0025	0.3788
				(2.91)	(-1.18)	(-1.39)	(-1.31)	(0.96)	(4.16)	(1.68)	(0.52)	(1.27)	(2.17)	(-0.47)	

Table 1.9. Alternative Cross-Sectional Regressions for Size Quintiles (cont.)

Panel C: *MV*3

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1803***					-0.0037**	0.0001	0.0009	0.0801**	0.0101***						0.2480
(4.67)					(-2.49)	(0.10)	(0.82)	(2.14)	(2.65)						
	1.2931***				-0.0124***	-0.0014*	0.0034***	0.1072***	0.0114***						0.3063
	(19.73)				(-6.52)	(-1.88)	(2.90)	(2.77)	(2.74)						
		-1.1094***			0.0064***	0.0015**	-0.0026**	0.0701*	0.0107**						0.2786
		(-19.45)			(4.69)	(2.05)	(-2.32)	(1.95)	(2.16)						
			0.2304***		-0.0044***	-0.0001	0.0012	0.0845**	0.0101***						0.2563
			(5.43)		(-2.93)	(-0.14)	(1.03)	(2.29)	(2.77)						
				0.2219***	-0.0037**	-0.0001	0.0012	0.0851**	0.0101***						0.2558
				(5.34)	(-2.55)	(-0.15)	(1.07)	(2.33)	(2.75)						
0.1427**					-0.0039**	0.0008	-0.0008	0.0973*	0.0057	0.0120	-0.3561	0.0000	-0.0022	-0.0028	0.3415
(2.54)					(-2.11)	(0.84)	(-0.53)	(1.68)	(1.04)	(1.31)	(-0.21)	(0.07)	(-1.61)	(-0.50)	
	1.2102***				-0.0151***	-0.0013	0.0013	0.1452***	0.0086	0.0106	-0.0393	0.0000	-0.0022*	-0.0023	0.3884
	(15.02)				(-6.68)	(-1.55)	(0.85)	(2.58)	(1.46)	(1.28)	(-0.03)	(-0.88)	(-1.86)	(-0.61)	
		-1.1539***			0.0071***	0.0020**	-0.0042***	0.0590	0.0079	0.0238***	-0.0196	0.0000	-0.0018	0.0004	0.3701
		(-15.31)			(3.79)	(1.97)	(-2.84)	(1.23)	(1.36)	(2.56)	(-0.01)	(0.37)	(-1.39)	(0.06)	
			0.1700***		-0.0045**	0.0007	-0.0005	0.0836	0.0058	0.0100	-0.7326	0.0000	-0.0026*	-0.0023	0.3462
			(2.97)		(-2.35)	(0.72)	(-0.34)	(1.44)	(1.08)	(1.07)	(-0.39)	(0.29)	(-1.85)	(-0.41)	
				0.1714***	-0.0050***	0.0007	-0.0003	0.0825	0.0059	0.0100	-0.6850	0.0000	-0.0026*	-0.0019	0.3461
				(3.12)	(-3.08)	(0.77)	(-0.22)	(1.44)	(1.11)	(1.07)	(-0.36)	(0.33)	(-1.86)	(-0.36)	

Table 1.9. Alternative Cross-Sectional Regressions for Size Quintiles (cont.)

Panel D: *MV*4

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1235***					-0.0009	-0.0020**	-0.0003	0.0743***	0.0176***						0.2747
(2.90)					(-0.65)	(-1.97)	(-0.33)	(2.80)	(4.25)						
	1.1921***				-0.0106***	-0.0027**	0.0016	0.1373***	0.0168***						0.3129
	(16.71)				(-6.23)	(-2.55)	(1.60)	(5.05)	(3.78)						
		-1.0660***			0.0091***	-0.0008	-0.0022**	0.0200	0.0191***						0.3052
		(-15.34)			(6.20)	(-0.87)	(-2.48)	(0.72)	(4.26)						
			0.1555***		-0.0014	-0.0021**	-0.0003	0.0760***	0.0179***						0.2796
			(3.51)		(-0.95)	(-2.10)	(-0.33)	(2.91)	(4.39)						
				0.1464***	-0.0011	-0.0021**	-0.0003	0.0736***	0.0177***						0.2788
				(3.45)	(-0.80)	(-2.11)	(-0.29)	(2.82)	(4.33)						
0.0604					-0.0035**	0.0008	-0.0004	0.0454	0.0118**	0.0141***	-1.0622	0.0002***	-0.0001	0.0011	0.3247
(1.40)					(-2.01)	(1.05)	(-0.41)	(1.46)	(2.37)	(2.59)	(-0.71)	(2.89)	(-0.11)	(0.32)	
	1.2138***				-0.0169***	-0.0004	0.0018*	0.1139***	0.0135***	0.0086	-1.1108	0.0001*	-0.0008	0.0030	0.3655
	(18.12)				(-7.76)	(-0.48)	(1.69)	(3.42)	(2.61)	(1.57)	(-0.76)	(1.90)	(-0.64)	(0.99)	
		-1.3461***			0.0107***	0.0011	-0.0025**	-0.0087	0.0104*	0.0208***	-0.7243	0.0002***	0.0009	-0.0007	0.3688
		(-20.48)			(5.84)	(1.34)	(-2.48)	(-0.29)	(1.94)	(3.51)	(-0.50)	(3.20)	(0.71)	(-0.20)	
			0.0590		-0.0028	0.0007	-0.0006	0.0436	0.0124***	0.0139**	-0.8885	0.0002***	-0.0003	0.0007	0.3306
			(1.21)		(-1.60)	(0.95)	(-0.54)	(1.47)	(2.57)	(2.53)	(-0.62)	(2.80)	(-0.22)	(0.20)	
				0.0599	-0.0040**	0.0007	-0.0007	0.0404	0.0122**	0.0140**	-0.9505	0.0002***	-0.0002	0.0007	0.3300
				(1.29)	(-2.35)	(0.87)	(-0.63)	(1.38)	(2.53)	(2.55)	(-0.67)	(2.77)	(-0.18)	(0.21)	

Table 1.9. Alternative Cross-Sectional Regressions for Size Quintiles (cont.)

Panel E: High *MV*5

Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.0340					0.0005	0.0016*	-0.0005	0.0997***	0.0085						0.3400
(0.90)					(0.27)	(1.84)	(-1.01)	(2.66)	(1.60)						
	1.2284***				-0.0121***	0.0000	0.0023***	0.1962***	0.0067						0.3746
	(19.13)				(-6.93)	(0.04)	(4.21)	(4.89)	(1.27)						
		-1.4379***			0.0121***	0.0028***	-0.0043***	-0.0151***	0.0127**						0.3795
		(-24.64)			(6.76)	(2.83)	(-7.97)	(-0.42)	(2.33)						
			0.0748*		0.0001	0.0013	-0.0002	0.1025***	0.0079						0.3460
			(1.74)		(0.04)	(1.56)	(-0.36)	(2.80)	(1.51)						
				0.0738*	-0.0006	0.0013	-0.0001	0.0996***	0.0080						0.3456
				(1.87)	(-0.36)	(1.53)	(-0.26)	(2.73)	(1.52)						
0.0183					-0.0021	0.0004	-0.0013*	0.0936*	0.0076	0.0039	4.1534	0.0002*	0.0013	-0.0115	0.4173
(0.29)					(-1.08)	(0.36)	(-1.95)	(1.74)	(1.10)	(0.58)	(1.25)	(1.91)	(0.66)	(-1.41)	
	1.4529***				-0.0169***	-0.0005	0.0011*	0.1644***	0.0067	0.0064	2.7185	0.0002**	0.0004	-0.0093	0.4539
	(13.61)				(-8.31)	(-0.46)	(1.67)	(3.16)	(0.95)	(0.95)	(0.84)	(2.10)	(0.23)	(-1.36)	
		-1.5488***			0.0135***	0.0012	-0.0043***	-0.0053	0.0112*	0.0062	0.5163	0.0002**	0.0019	-0.0076	0.4632
		(-19.47)			(6.89)	(1.26)	(-6.74)	(-0.10)	(1.65)	(0.97)	(0.22)	(2.29)	(1.02)	(-1.06)	
			0.0208		-0.0018	0.0004	-0.0013*	0.0927*	0.0078	0.0047	1.2174	0.0002**	0.0013	-0.0128	0.4209
			(0.35)		(-0.90)	(0.44)	(-1.95)	(1.84)	(1.21)	(0.72)	(0.44)	(2.04)	(0.71)	(-1.61)	
				0.0241	-0.0025	0.0004	-0.0013*	0.0912*	0.0071	0.0043	1.3899	0.0002**	0.0014	-0.0138*	0.4212
				(0.44)	(-1.30)	(0.41)	(-1.93)	(1.81)	(1.12)	(0.66)	(0.50)	(2.06)	(0.76)	(-1.71)	

Table 1.10. Bivariate Sorts on *Range* and *SD*

The bivariate quintiles are formed for every month in the research period by sorting the country-industry indexes based on *SD* (*Range*). Then, the indexes in each *SD* (*Range*) quintile are further sorted based on *Range* (*SD*). Equal- and value-weighted averages of returns across all *SD* (Range) quintiles within a *Range* (*SD*) quintile are calculated to find the returns on average *SD* (Range) portfolios, i.e., $SD_{\text{ew-Avg}}$ and $SD_{\text{vw-Avg}}$ ($Range_{\text{ew-Avg}}$ and $Range_{\text{vw-Avg}}$). Panel A (B) shows the returns for the average *SD* (*Range*) portfolios. 5-1 *Range* (*SD*) portfolio is the zero-cost arbitrage portfolio, which longs the portfolio with the highest *Range* (*SD*) and shorts the one with the lowest. For the 5-1 long-short portfolios, average raw return differences and Jensen alphas from the international versions of the ICAPM, the Fama-French three-factor model (FF3) and the Fama-French-Carhart four-factor model (FFC4) are presented in the last four rows of the panels, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Indexes are sorted on *Range* after controlling for *SD*			Panel B: Indexes are sorted on *SD* after controlling for *Range*		
	$SD_{\text{ew-Avg}}$	$SD_{\text{vw-Avg}}$		$Range_{\text{ew-Avg}}$	$Range_{\text{vw-Avg}}$
1 Low *Range*	0.0133	0.0125	1 Low *SD*	0.0081	0.0062
2	0.0122	0.0095	2	0.0100	0.0071
3	0.0135	0.0115	3	0.0121	0.0085
4	0.0131	0.0116	4	0.0149	0.0138
5 High *Range*	0.0159	0.0177	5 High *SD*	0.0226	0.0237
5-1*Range*	0.0026^{**}	0.0052^{*}	5-1*SD*	0.0145^{***}	0.0174^{***}
	2.09	1.66		7.18	4.81
α_{CAPM} (5-1)	0.0023^{**}	0.0051^{*}	α_{CAPM} (5-1)	0.0125^{***}	0.0156^{***}
	2.01	1.69		8.66	5.19
α_{FF3} (5-1)	0.0009	0.0027	α_{FF3} (5-1)	0.0085^{***}	0.0102^{***}
	0.83	1.03		6.82	3.77
α_{FFC4} (5-1)	0.0008	0.0021	α_{FFC4} (5-1)	0.0085^{***}	0.0097^{***}
	0.77	0.80		6.71	3.56

CHAPTER 2

ARE INDEX-RETURN PREDICTORS THE SAME ACROSS REGIONS?

2.1. Introduction

This dissertation chapter examines the significance of the nineteen index attributes as well as the newly proposed total volatility measure of *Range*, which are examined in the previous chapter, for different regions. More specifically, by dividing the total sample of country-industry indexes into six different regions as North America, Europe, Asia-Pacific, South America, MENA (Middle East and North Africa), and Japan, new empirical evidences can be obtained about the potential predictors of international index returns across different regions.

In the first dissertation chapter, the total sample of the country-industry indexes are used as a proxy for world market and assumed as fully integrated with the global market and thus, the international versions of the asset-pricing models are used. In other respects, there are several studies indicating that the significance of the trading strategies can change across stock markets and regions depending on their financial market development and market segmentation/integration[7]. In addition, regions have different characteristics about their stock market conditions, market regulations and economic activities. These differences in characteristics cause changes in the degree of integration of the regions into global markets across regions. Therefore, the regions, which are mostly segmented, are dominated by the regional factors in the explanation of index returns while the regions, which are mostly integrated with the global market, are highly affected by the global factors (Umutlu et al. 2010a, 2010b). In this dissertation chapter, I take into account the different characteristics of the regions, which may lead to the potential market

[7] Some of the studies focused on the market segmentation/integration are as the following: Errunza & Losq (1985), Bekaert & Harvey (1995), Foerster & Karolyi (1999), Bekaert, Harvey, & Lumsdaine (2002), De Jong & De Roon (2005), Carrieri, Errunza, & Hogan (2007), Umutlu, Akdeniz, & Altay-Salih (2010a), Umutlu, Altay-Salih, & Akdeniz (2010b), Bekaert, Harvey, Lundblad, & Siegel (2011), Hou, Karolyi, & Kho (2011), Zaremba (2016c), Umutlu & Bengitöz (2020).

segmentation of the regions, and therefore, perform the regional versions of the asset-pricing models (Bekaert, Hodrick, & Zhang, 2009). The regional asset-pricing models provides the index returns to be adjusted to both global and regional risk factors that may change across regions. As a result, it can be investigated that whether the effect of an index attribute can exist in specific regions. In sum, regional asset-pricing models aim to investigate that whether the trading strategies based on nineteen index attributes (*Range*: the difference between maximum and minimum daily index returns within a month; *MAX*: the maximum daily index return within a month; *MIN*: the negative of the minimum daily index return within a month; *SD*: the standard deviation of index returns; *IVOL*: the index-specific idiosyncratic volatility; *BETA*: the market beta from the ICAPM; *TSKEW*: the total skewness of the index returns; *ISKEW*: the idiosyncratic skewness; *MV*: the market capitalization; *EP*: the earnings-to-price ratio; *DY*: the dividend yield; *EBITDA/EV*: the cash earnings-to-enterprise value; *IntMom*: the intermediate-term momentum; *StMom*: the short-term momentum; *OP*: the operating profitability; *ES*: the earnings surprise; *ROE*: the return on equity; *INV*: the investment; and *NSI*: the net share issuance) generate abnormal returns across different regions.

Similar with the previous chapter, the significance of these nineteen index attributes is tested for each region by performing both portfolio-level analysis and index-level cross-sectional regressions. Portfolio analysis provides examining the whether the zero-cost trading strategy based on each index attribute provides significant raw and risk-adjusted returns. Unlike the previous chapter, which assumes the total sample is fully integrated and thus, uses the international versions of the asset-pricing models, this dissertation chapter takes into consideration of the potential segmentation of the regions and uses the regional versions of the asset-pricing models, which are the International CAPM (ICAPM), the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4), in line with the study of Bekaert, Hodrick, and Zhang (2009). The regional versions of the asset-pricing models enable us to estimate the regional index returns that are adjusted to both global and regional risk factors. Furthermore, Fama-MacBeth cross-sectional regressions are also performed to investigate the significance of the relationship between the relevant index attribute and the future index returns under the control of several index attributes simultaneously.

The results of the univariate portfolio sorts show that all measures of total volatility as well as *Range*, and the idiosyncratic volatility have significant explanatory effects on the returns of the country-industry indexes from Europe, Asia-Pacific, South America, and Japan. On the other hand, in North America and MENA, only *MAX* and *MIN* survive among all volatility measures. Therefore, it can be concluded that *MAX* and *MIN* persistently significant regardless of the region. Moreover, the size effect and the value effect, depending on the measurement approach, significantly exist for all regions, except that in Japan only size effect is valid. Momentum effect either measured as intermediate-term or short-term have significant effects on index returns of North America, Europe, and MENA. Even though the operating profitability is insignificant for all regions, the other measures of profitability provides abnormal returns for Europe and Asia-Pacific depending on the measure used in trading strategies. In addition, both measures of skewness have significant explanatory power on the index returns only for the European country-industry indexes. Furthermore, the results of the Fama-MacBeth regressions support the results of the portfolio analyses. Unlike the portfolio analyses, the index-level cross-sectional regression results point out that skewness measures either as total skewness or idiosyncratic skewness significantly explains future index returns across all regions depending on the regression specification. In addition, the probability effect measured with earnings surprise have significant effect on expected returns of Japanese country-industry indexes. Lastly, the regression results suggest that the usage of the alternative measures of the value, skewness, momentum, and profitability effects rather than the fundamental ones does not cause remarkable changes in the results.

The second dissertation chapter is organized as follows. Section 2.2 provides the description of the data and its sources. Section 2.3 summarizes the anomalies. Section 2.4 describes the methodologies for the portfolio-level analyses and the index-level cross-sectional regressions. Section 2.5 presents the results. Section 2.6 concludes the dissertation chapter.

2.2. Data and Methodology

This dissertation chapter extends the sample of the previous chapter by enlarging the country-industry index data with the usage of more countries and more recent data. In other words, the number of countries is increased from 37 to 51 while the end date of the whole sample is extended from 07.2015 to 07.2017. The dataset includes the same variables as mentioned in the first dissertation chapter from Datastream. Similarly, for the sample of country-industry indexes, the industry definitions of the Industry Classification Benchmark (ICB) of FTSE[8] are used. The detailed explanations are made in the first dissertation chapter. Differently, daily and monthly risk-free rate is obtained by using the one-month Treasury bill rate from Kenneth R. French's data library[9].

The whole sample of country-industry indexes are divided into six different regions to examine the performance of the trading strategies for each anomaly across different regions. These regions are North America (US, Canada), Europe (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Norway, Portugal, Spain, Sweden, Switzerland, UK, Czech Republic, Hungary, Poland, Turkey), Asia-Pacific (Australia, Hong Kong, New Zealand, Singapore, China, India, Indonesia, Korea, Malaysia, Pakistan, Philippine, Russia, South Africa, Taiwan, Thailand, Vietnam), South America (Argentina, Brazil, Chile, Mexico), MENA - Middle East and North Africa - (Bahrain, Egypt, Israel, Kuwait, Morocco, Oman, Qatar, UAE), and Japan.

In this dissertation chapter, I use the same index attributes as in the previous chapter, but, all index attributes are calculated for each region separately. In this section, I only summarize the definitions of the anomalies.

The first group of variables are related with the volatility measures, which are total, systematic, and idiosyncratic volatility. *Range*, which is newly proposed as an alternative proxy for total volatility in the previous chapter, is defined as the difference between the maximum and minimum daily returns within a month. The other measures of total volatility are *MAX*, the maximum daily return within a month, and *MIN*, the negative of the minimum daily return within a month. *MAX* and *MIN* are used as proxies for upside risk and downside risk, respectively. *SD*, which is the traditional total volatility measure, is the standard deviation of returns within a month. *IVOL* is the idiosyncratic volatility

[8] The supersector definitions and the ICB structure are comprehensively documented in the following link: www.icbenchmark.com.
[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

defined as the standard deviation of the error terms obtained from the ICAPM. *BETA* is the market beta from the ICAPM.

The second group of variables are related to skewness measures. *TSKEW* is the total skewness, which is measured as the skewness of the daily return data of the previous one year. *ISKEW* is the idiosyncratic skewness, which is defined as the skewness of the daily error terms in Equation (1.5) in the previous year

The next group of variables are the measures of the size and value effects. *MV* is the market capitalization value in billion dollars. The measures of the value effect are as the following: *EP*, earnings-to-price ratio, is the division of the earnings per share by the share price; *DY*, dividend yield, is the dividend per share as a percentage of the share price; and *EBITDA/EV* is the earnings before interest, taxes, depreciation, and amortization over enterprise value.

The third group of variables includes the measures of the momentum effects, *IntMom* is the cumulative monthly returns of the previous 11-month period covering months from *t*-12 to *t*-2 while *StMom* is the cumulative monthly returns of the previous 6-month period covering months from *t*-6 to *t*-2.

The fifth group of variables are related to profitability measures. *OP* is the operating profitability and it is equal to the difference between the earnings before interest and taxes (*EBIT*) and interest that is divided by the book equity; *ROE* is the return on equity; *ES* is the earnings surprise and it is defined as the changes in analysts' estimates of earnings.

The last group of variables includes the stand-alone ones. *INV* is the investments representing the changes in total assets from years *t*-2 to *t*-1 and *NSI* is the net share issuance.

Table 2.1 shows the regional version of the descriptive statistics of nineteen index attributes for country-industry indexes including 19 industries specified for 51 countries. The descriptive statistics are calculated by following two steps. In the first step, the monthly cross-sectional average of each index attribute across indexes are calculated. In the second step, the time-series averages of the cross-sectional means are calculated over the months in the whole sample period. These steps are repeated for each region Moreover, the standard deviation, maximum, and minimum values are calculated by using the monthly time-series data of cross-sectional means. According to the basic statistics, the index attributes of *MV*, *ROE*, *BETA*, *OP* in all regions; *TSKEW* in all regions, except North America; *ISKEW* in Europe, Asia-Pacific, South America, and MENA; *ES* in South America, *EBITDA/EV* in North America, Europe, South America, and Japan; *INV* in North America, Asia-Pacific, South America, and MENA; *NSI* in MENA have the highest standard deviation values and correspondingly the highest mean values. In a similar way, the range between the maximum and minimum values of these index attributes are also higher than the other attributes. Moreover, the mean value for *MV* is the highest for North America since it is highly integrated with the global markets.

< Table 2.1 here >

Table 2.2 presents the correlation matrix for nineteen index attributes for each region. The correlation matrix for regions are calculated based on a method with two steps. In the first step, cross-correlations among index attributes across indexes are calculated for every month. Then, in the second step, the cross-correlations are time-series averaged over the months in the sample period. The Panels A to F in Table 2.2 show the correlation analyses for each region. The results of the correlation analyses point out that similar with the previous chapter, *Range* is highly correlated with *SD* as well as other total volatility measures of *MAX* and *MIN*. Moreover, *IVOL* is also highly correlated with the all measures of total volatility. These correlations are robust to all six different regions. On the other hand, even though the high correlations between the combinations of *Range–SD–IVOL*, *MAX-MIN*, *EP-DY*, *IntMom-StMom*, and *OP-ROE* have minor increase or decrease in magnitude compared to global analyses in the previous chapter, they are still not included in the same regression specification at the same time to make the results comparable with the previous chapter and eliminate the multi-collinearity problem in the regression analyses.

< Table 2.2 here >

2.2.1. Portfolio Analyses

In this dissertation chapter, the univariate portfolio analysis is performed for each index attribute for the country-industry indexes of each region: North America, Europe, Asia-

Pacific, North America, MENA, and Japan, respectively. Similar with the previous chapter, quintile portfolios are formed by sorting the indexes based on each index attribute. As a result, portfolio 1 (5) includes the country-industry indexes with the lowest (highest) values of the related attribute. Thereafter, it is tested that whether the zero-cost arbitrage portfolios, constructed based on these extreme value portfolios, generate significant raw and risk-adjusted returns.

The significance of the risk-adjusted returns is examined by testing whether the Jensen alphas from several asset-ricing models are statistically different from zero. In the first dissertation chapter, since it is assumed that the total sample of country-industry indexes are fully integrated with the global market, the international versions of the asset pricing models are used. On the other hand, in this dissertation chapter, the potential market segmentation/integration of the regions is taken into consideration and the Jensen alphas are estimated by performing the regional versions of the asset pricing models. The degree of integration of the regions into global market changes depending on the different aspects about their stock market conditions, market regulations and economic activities. More specifically, in the regions that are mostly segmented, regional factors play an important role in the explanation of index returns while in the regions that are mostly integrated with the global market the effect of global factors can dominate the effect of regional factors on index returns (Umutlu et al., 2010a, 2010b). Bekaert et al. (2009) developed a model that includes both global and regional factors in the asset-pricing models. It is stated that the model takes into account both global and regional factors and so, exposures to these risk factors can be captured for the markets that are fully or partially integrated with the world market or for the markets that are regionally segmented. In line with the study of Bekaert et al. (2009), this chapter performs the regional versions of the International CAPM (ICAPM), the Fama-French three-factor model (FF3), and the Fama-French-Carhart four-factor model (FFC4), which estimate the country-industry index returns adjusted to both global risk factors and regional risk factors that may change across regions. The regional version of the ICAPM is formulated as in the Equation (2.8):

$$R_{5-1t} = \alpha_{CAPM} + \beta_W R_{Wt} + \beta_R R_{Rt} + \varepsilon_t \tag{2.8}$$

where $R_{5\text{-}1t}$ shows the return difference between the extreme portfolios of 5 and 1 in month t; R_{Wt} shows the excess return for the world market portfolio, represented by the Datastream World Market Index, in month t; R_{Rt} shows the regional orthogonalized return with respect to the world market return; and ε_t shows the error term. The intercept coefficient (α_{ICAPM}) shows the risk-adjusted excess return that is adjusted to both global and regional risk factors. Moreover, R_{Rt} is estimated by regressing the monthly values of the regional excess returns on the world market portfolio excess returns for the whole sample period. The time-series residuals of this regression are defined as the regional orthogonalized return and defined as R_{Rt} in Equation (2.8). In addition, the monthly regional excess returns are calculated by taking the value-weighted averages of the country-industry indexes in the relevant region with the use of the market capitalization values from the previous month.

The next model is the regional version of the FF3 model as shown in the following:

$$
\begin{aligned}
R_{5-1t} = \alpha_{FF3} + \beta_W R_{Wt} + \beta_{WSMB} R_{WSMBt} + \beta_{WHML} R_{WHMLt} + \beta_R R_{Rt} \\
+ \beta_{RSMB} R_{RSMBt} + \beta_{RSMB} R_{RHMLt} + \varepsilon_t
\end{aligned}
\tag{2.9}
$$

where R_{WSMBt} shows the world small-minus-big factor, defined as the excess raw return difference between the extreme value portfolios sorted based on market value of country-industry indexes in month t; R_{WHMLt} shows the world high-minus-low factor, defined as the excess raw return difference between the extreme value portfolios sorted based on earnings-to-price ratio of country-industry indexes in month t; R_{RSMBt} is the regional orthogonalized size factor; R_{RHMLt} is the regional orthogonalized value factor. As explained in the ICAPM, to obtain these regional orthogonalized factors; the time-series observations of the regional *SMB* factor are regressed on the world *SMB* factor while the regional *HML* factor are regressed on the world *HML* factor over the full sample period. The residuals from these regressions are used as the regional orthogonalized *SMB* and *HML* factors in Equation (2.9).

Our last model is the regional version of the FFC4 model, which includes Carhart's (1997) momentum factor:

$$R_{5-1t} = \alpha_{FFC3} + \beta_W R_{Gt} + \beta_{WSMB} R_{WSMBt} + \beta_{WHML} R_{WHMLt} + \beta_{WWML} R_{WWMLt} + \beta_R R_{Rt} + \beta_{RSMB} R_{RSMBt} + \beta_{RSMB} R_{RHMLt} + \beta_{RWML} R_{RWMLt} + \varepsilon_t \quad (2.10)$$

where R_{WWMLt} is the world winner-minus-loser factor, which is the excess raw return difference between the highest and lowest intermediate-term momentum quintiles of country-industry indexes in month *t*; R_{RWMLt} is the regional orthogonalized momentum factor. Similarly, R_{RWMLt} is the residuals from the regression that regresses the time-series observations of the regional *WML* factors on the world *WML* factor. The other components of the regression are previously defined.

The Jensen's alphas obtained from the regional models are used to examine whether the extreme portfolios generate statistically significant abnormal risk-adjusted returns. The hypothesis for the Jensen's alpha is defined as

$H_0: \alpha_0 = 0$

$H_1: \alpha_0 \neq 0$

Rejecting the null hypothesis means that the zero-cost arbitrage trading strategy for the relevant index attribute provides significant abnormal risk-adjusted returns. More specifically, it can be suggested that the relevant index attribute significantly affects the country-industry index returns that is free from the effect of systematic risk factors.

2.2.2. Index-level Cross-Sectional Regression Analysis

The index-level cross-sectional regression Equations (2.11) and (2.12), which are arranged depending on the results of the correlation analyses and the univariate portfolio analyses in the previous chapter, are performed for each region to eliminate the multicollinearity problem and make the results comparable with the previous chapter.

$$R_{it+1} = \beta_{0t} + \beta_{1t} Range_{it} + \beta_{2t} MAX_{it} + \beta_{3t} MIN_{it} + \beta_{4t} SD_{it} + \beta_{5t} IVOL_{it} + \beta_{6t} BETA_{it} + \beta_{7t} TSKEW_{it} + \beta_{8t} MV_{it} + \beta_{9t} EP_{it} + \beta_{10t} IntMom_{it} + \beta_{11t} EBITDA/EV_{it} + \beta_{12t} OP_{it} + \beta_{13t} ES_{it} + \beta_{14t} INV_{it} + \beta_{15t} NSI_{it} + \varepsilon_{it} \quad (2.11)$$

$$
\begin{aligned}
R_{it+1} = \beta_{0t} &+ \beta_{1t}Range_{it} + \beta_{2t}MAX_{it} + \beta_{3t}MIN_{it} + \beta_{4t}SD_{it} + \beta_{5t}IVOL_{it} \\
&+ \beta_{6t}BETA_{it} + \beta_{7t}ISKEW_{it} + \beta_{8t}MV_{it} + \beta_{9t}DY_{it} \\
&+ \beta_{10t}StMom_{it} + \beta_{11t}EBITDA/EV_{it} + \beta_{12t}ES_{it} \\
&+ \beta_{13t}ROE_{it} + \beta_{14t}INV_{it} + \beta_{15t}NSI_{it} + \varepsilon_{it}
\end{aligned} \tag{2.12}
$$

where R_{it+1} indicates the realized return on *i*. international index in month *t*+1 and all index attributes are the ones obtained from month *t*. Lastly, ε_{it} shows the error term. Moreover, some nested versions of the index-level cross-sectional regressions will be run for each month in the whole sample period and for each region separately.

After the regression analyses, the significance of the effect for the relevant index attribute on index returns is investigated in the average time period as explained in the previous chapter, in Section 1.4.2.

2.3. Results

2.3.1. Regional Portfolio Analyses

Table 2.3 shows the equal-weighted average monthly returns on the quintile portfolios for each index attribute across six different regions, which are North America, Europe, South America, Asia-Pacific, MENA, and Japan. In addition, the average raw returns and the Jensen alphas from the regional versions of the ICAPM (α_{ICAPM}), the FF3 (α_{FF3}) model, and the FFC4 (α_{FFC4}) model for the zero-cost arbitrage portfolios are also presented. All t-statistics are estimated based on the methodology of Newey-West (1987).

For the country-industry indexes in North America, the null hypothesis indicating that the equal-weighted mean returns of extreme value portfolios are equal to each other is rejected for the volatility measures of *MAX* and *MIN*. As a result, it can be stated that the trading strategies based on *MAX* and *MIN* can generate significant raw excess returns of 0.0304 and -0.0305 with the corresponding t-statistics of 12.40 and -13.04, respectively. In addition, the hypothesis that the Jensen alpha is equal to zero is rejected for all the models of risk-adjustment at %1 significance level, indicating there are persistently strong *MAX* and *MIN* effects on the country-industry index returns of North America. In other words, zero-cost arbitrage portfolios based on *MAX* and *MIN* earn abnormal returns that are free from the effect of global and regional risk factors. On the other hand, the trading strategies based on other index attributes do not have significant both raw excess and risk-adjusted returns at the same time, except the anomalies of *MV*, *EP*, *IntMom*, and *NSI*. Some of the trading strategies provide some significant alphas but the significance of the alphas changes across benchmark models, they are not persistent (*IVOL* only for α_{ICAPM}, *ES* only for α_{FFC4}).

< Table 2.3 here >

The equal-weighted portfolio results of European country-industry indexes provide evidence for the existence of more anomalies. All volatility measures (*Range*, *MAX*, *MIN*, *SD*, *IVOL*) provide highly significant raw and risk adjusted returns indicating that they have powerful explanatory effects on expected index returns. Moreover, the trading strategies based on *MV*, *EP*, *DY*, *IntMom*, *StMom*, *ISKEW*, *TSKEW*, *EBITDA/EV*, *ES* (except the alpha from FFC4), *NSI*, and *ROE* earn not only significant raw returns but also risk-adjusted returns, regardless of the model used in the estimation of Jensen alphas. Therefore, these variables have the potential to influence the cross-section of European index returns. Furthermore, even though the trading strategies constructed based on *BETA* and *INV* do not provide significant raw excess returns, their risk-adjusted returns from ICAPM and all of the benchmark models are significant, respectively. On the other hand, the zero-cost portfolio formed based on *OP* generate neither raw returns nor risk-adjusted returns for all benchmark models.

The results for equal-weighted Asia-Pacific portfolios are almost similar with the results of Europe, except for a few slight differences. Unlike European country-industry indexes, the anomalies of *IntMom*, *StMom*, *ISKEW*, and *TSKEW* do not exist in Asia-Pacific. Moreover, *ROE* does not generate significant raw returns while it provides evidence for abnormal risk-adjusted returns only for the FF3 model. The trading strategy based on *OP* still do not earn significant raw and risk-adjusted returns for all benchmark models. For the remaining index attributes not all risk-adjusted and raw returns are significant. As a result, it can be concluded that the zero-cost arbitrage portfolios based on all volatility measures, value measures, and the size effect provide consistently significant raw and risk adjusted returns from three different benchmark models.

The raw return and risk-adjusted return differences between the extreme value portfolios based on *Range*, *MAX*, *MIN*, *SD*, *IVOL*, and *MV* are persistently significant for the country-industry indexes of both South America and Japan. Differently, the trading strategy based on *DY* is persistently earn abnormal returns in South America while it generates risk-adjusted returns only for the benchmark models of FF3 and FFC4 in Japan. Furthermore, the anomalies of *INV* and *EBITDA/EV* only exist for the country-industry indexes of South America. Moreover, there is not any evidences for significant raw returns and Jensen alphas for the long-short portfolios of the remaining index attributes (*BETA*, *EP*, *IntMom*, *StMom*, *ISKEW*, *TSKEW*, *OP*, *ES*, *NSI*, and *ROE*) in these regions.

The results for MENA indicate that *Range* generate neither raw returns nor risk-adjusted returns, which is similar with the results of North America. On the other hand, there are persistent significant trading strategies based on *MAX*, *MIN*, *MV*, *EP*, *DY*, *StMom*, *ISKEW*, and *EBITDA/EV*. Different from other regions, the zero-cost arbitrage portfolios of *SD* and *IVOL* only generate significant raw excess returns; however, the Jensen alphas do not survive under all benchmark models. Furthermore, the significance of the Jensen alphas of *IntMom*, *TSKEW*, *NSI*, and *ROE* change depending on the model of risk-adjustment. Lastly, the anomalies of *OP*, *INV*, and *ES* do not have significant effects on raw and risk-adjusted returns.

< Table 2.4 here >

Table 2.4 presents the value-weighted portfolio results for six regions with the Newey-West (1987) t-statistics in the parenthesis. Similar with the equal-weighted portfolio results, the anomalies of *MAX* and *MIN* continue to exist for all regions without any exception when value-weighted portfolio analyses are performed. It is an important finding that the highly significant t-statistics, which remain persistently significant for all Jensen alpha models, point out that *MAX* and *MIN* are strong anomalies worldwide.

Furthermore, it is also word-emphasizing that the *Range* effect, which is significant for equal-weighted portfolios in all regions, except North America and MENA, is no more significant for value-weighted portfolios in South America according to both raw and risk-adjusted returns. Different from the equal-weighted portfolio results of North America, *Range* effect becomes significant when value-weighted trading strategy is performed.

Moreover, in Japan, *Range* still has a significant explanatory power on value-weighted raw excess and risk-adjusted returns. On the other hand, even though the raw returns of *Range* in Europe and Asia-Pacific are significant, their risk-adjusted returns are consistently insignificant, regardless of the model used to obtain Jensen alphas. Unlike, in MENA, *Range* generates abnormal risk-adjusted returns for all benchmark models while its raw excess return is insignificant. The significance of the *Range* effect for equal-weighted portfolios of Japan also persistently exist for value-weighted portfolios.

The anomalies of *SD* and *IVOL*, which are detected for equal-weighted portfolios in the regions of Europe, Asia-Pacific, and South America, produce significant raw excess returns and risk-adjusted returns only for the regional version of ICAPM, except that for Asia-Pacific none of the benchmark models are significant. Moreover, in North America, while *SD* is consistently significant, *IVOL* does not provide significant results. Additionally, for the country-industry indexes in MENA, the trading strategies based on *SD* and *IVOL* generate neither raw returns nor risk-adjusted returns. On the other hand, the significant effects of *SD* and *IVOL* continue to be significant for value-weighted portfolios of Japan.

The persistently significant trading strategies based on all skewness measures for equal-weighted portfolios of Europe and MENA do not survive for value-weighted portfolios, thus, become insignificant regardless of the regions. On the other hand, similar with the equal-weighted portfolios, the size effect still consistently provides significant value-weighted raw and risk-adjusted returns from all three asset-pricing models for every region. Furthermore, the value effect slightly loses its strong predictive ability for the regions of Europe, Asia-Pacific, and MENA. More specifically, all measures of the value effect, *EP*, *DY*, *EBITDA/EV*, are persistently significant in equal-weighted portfolios whereas in Europe and Asia-Pacific only *EP* and *DY*; in MENA only *DY* survive for the value-weighted portfolios. In addition, in South America, there is still significant value effect when measured as *DY*. Although the equal-weighted portfolios of Japan do not have any significant measures of the value effect, the value-weighted portfolios based on *EBITDA/EV* provides significant raw and risk adjusted returns for all benchmark models. The significant value effect based on *EP* in North America almost loses its predictive ability for the value-weighted portfolios.

The strong momentum effect for the regions of North America, Europe, and MENA sharply decreases and *IntMom* survive only in North America and Europe; *StMom* in MENA and Europe depending on the asset-pricing models. The rest of the anomalies, profitability measures and the stand-alone measures, which are exist for equal-weighted portfolios in some regions depending on the model of risk-adjustment, lose their significance for the value-weighted portfolios and do not survive in some benchmark models.

Overall, the results from Tables 2.3 and 2.4 indicate that there are noteworthy differences among the regions. The number of significant anomalies changes depending on the benchmark model used to estimate Jensen alphas even in the same region. The anomalies of *MAX* and *MIN* are persistently significant for all regions under all cases (weights of the portfolio and benchmark models). Moreover, the effect of *OP* does not provide abnormal returns regardless of the benchmark models and regions. However, the reason of these different results is not only caused by the regional factors, but also caused by depending on the weight of the portfolio since the results across the equal- and value-weighted portfolios are different even in the same region. Furthermore, depending on the benchmark model, the number of significant anomalies in equal-weighted portfolio trading strategies is more than the ones in value-weighted portfolios. The reason might be that in equal-weighted portfolios, the indexes having small market capitalization values can have a more voice on the results than the indexes having large market capitalization values. Therefore, it can be stated that some anomalies can be only significant for the indexes having small market capitalization values.

2.3.2. Regional Cross-Sectional Regression Analysis

The portfolio analyses results indicate that *Range*, *MAX*, *MIN*, *SD*, *IVOL*, *BETA*, *MV*, *EP*, *DY*, *IntMom*, *StMom*, *ISKEW*, *TSKEW*, *OP*, *INV*, *EBITDA/EV*, *ES*, *NSI*, and *ROE* significantly affect international index returns. In this section, the persistency of the significant results of the portfolio analyses are examined by performing index-level cross-sectional regression analysis. Since the correlation analyses indicate that the sets of *Range-MAX-MIN-SD-IVOL*, *EP-DY*, *IntMom -StMom*, *ISKEW-TSKEW*, and *OP-ROE* are highly correlated, these sets are not included in the regression equations of (2.11) and

(2.12) simultaneously. Similar with the previous chapter, the regression equation (2.11) is referred as the main equation that includes the index attributes of *EP*, *IntMom*, *TSKEW*, and *OP* as the fundamental measures of the value, momentum, skewness, and probability effect and the counterparts of these measures, *DY*, *StMom*, *ISKEW*, and *ROE*, are used in the alternative regression equation (2.12).

Tables 2.5 and 2.6 show the results of the cross-sectional regressions for six regions. For every panel of these tables, the first five rows present the results for the regression specifications with fewer anomalies while the last five rows present the results for the specifications including *EBITDA/EV*, *ES*, *NSI*, *ROE*, *OP*, and *INV*. For the first five regression specifications, the earliest start date is April 1974 and February 1974 for Tables 2.5 and 2.6, respectively, which extend to July 2017. On the other hand, for the last five regression specifications, as the data needed to construct the relevant anomalies, the earliest start date is September 1985 for both Tables 2.5 and 2.6. The estimation periods of the cross-sectional regressions change across regions due to the data availability in the calculations of the anomalies. In Tables 2.5 and 2.6, the time-series averages of the slope coefficients and the corresponding adjusted t-statistics based on Newey-West (1987) are presented.

< Table 2.5 here >

In Table 2.5, the results of North America in Panel A are noteworthy that only *IntMom* effect is persistent on index returns. *IntMom* has a significant positive coefficient estimates for all regression specifications, even though the inclusion of other anomalies and the use of a more recent data in the last five specifications. Moreover, the results provide some significant slope estimates for *BETA*, *MV*, and *EP*, but these anomalies do not survive for all specifications. Furthermore, the volatility measures do not provide significant results, except for *MAX* and *MIN* effects, which are used as proxies for the total volatility. Consequently, the only index-level anomalies that exist persistently in North America are *IntMom*, *MAX*, and *MIN*.

For the country-industry indexes of Europe, the total volatility measures of *Range*, *SD*, *MAX*, and *MIN* are highly significant with positive slope coefficient estimates in all the regression specifications they are included, except that *MIN* has negative coefficient estimates. It means that total volatility measures have strong powers in explaining future index returns. Moreover, the coefficient estimates of *SD* are slightly larger than the ones for *Range*, which suggest that *SD* includes more information about future index returns than *Range*. On the other hand, even though the magnitudes of the coefficient estimates of *MAX* and *MIN* are considerably high, the total volatility measures of *SD* and *Range*, which are estimated by using all the daily return in the past month, might reveal much information about future index returns rather than just the maximum and minimum return of that month. In addition, the highly positive significant coefficient estimates of *IVOL* point out that index-specific idiosyncratic volatility strongly affects future index returns. Furthermore, the results show that *MV*, *EP*, *IntMom*, and *EBITDA/EV* are almost persistently significant, which are consistent with the portfolio-level analyses results. As a result, it can be concluded that European country-industry indexes are affected by the volatility, value momentum anomalies.

In Panel C, the results of Asia-Pacific indexes also provide evidence for the existence of positive significant effects of total volatility and idiosyncratic volatility anomalies of *Range*, *SD*, and *IVOL* on future index returns. Moreover, *MAX*, and *MIN* again have highly significant coefficient estimates in magnitude. Moreover, there is also a persistent value effect measured as *EP*. On the other hand, *IntMom* is only significant when the regression specifications include high number of anomalies. Moreover, the size and skewness (measured as *TSKEW*) effects and *BETA* do not persistently survive for all regression specifications. These results support the results of portfolio analyses, except for *TSKEW*. In conclusion, it can be inferred that there are persistent volatility and value effects and also in some cases size, momentum, skewness and beta effect on the cross-section of expected returns on the country-industry indexes of Asia-Pacific.

In the country-industry indexes of South-America, similar with previous regions, total volatility measure and idiosyncratic volatility are strongly significant. Moreover, the anomalies of *BETA*, *MV*, *EP*, *TSKEW*, and *EBITDA/EV* provide some significant results when they are included in the regression with either *MAX* or *MIN*. In addition, *NSI* is only slightly significant when it is included in the regression with *Range*. These results indicate that rather than volatility measures, value measures, total skewness, and *BETA* have power in the explanation of index returns.

The results of MENA also show that volatility measures are consistently significant. Moreover, *EP* almost in all specifications and *IntMom* in the first four specifications, which include fewer variables in the regressions, provide persistently significant regression coefficients. Moreover, in the regression specifications including *MAX* or *MIN*, the slope coefficients of the anomalies of *BETA* and *MV* are also significant. Therefore, beyond the volatility measures, in some cases the index attributes of *BETA*, *MV*, *EP*, and *IntMom* have significant information about the future expected returns on the country-industry indexes of MENA.

Lastly, in Japan, the results of volatility measures support the results of previous regions. Differently, in Japan, *TSKEW* almost persistently survive in all regression specifications. Moreover, in the last five regression specifications, which are run with higher number of index attributes, *ES* provides positive significant slope coefficient for all regression specifications. Moreover, *EP* is also almost persistently significant for the regression specifications that are run with a smaller number of anomalies, except the one with *MIN*. Furthermore, for the regression specifications including either *MAX* or *MIN*, the anomalies of *BETA*, *MV*, and *NSI* provide at least one evidence for the existence of their significant effects on future expected returns.

In summary, total volatility measures of *Range*, *SD*, *MAX*, and *MIN* and idiosyncratic volatility, *IVOL*, provide persistently significant estimates of coefficients in all regression specifications they are included, regardless of the regions. It can be inferred that volatility measures are not affected by the global and regional factors, which supports the results of portfolio-level analyses. Moreover, the significant *IntMom* effect exists persistently in the regions of North America, Europe, and Asia-Pacific. On the other hand, in Asia-Pacific and MENA, *IntMom* is widely seen for the regression specifications run with higher and a smaller number of variables, respectively. Furthermore, there is almost a persistent value effect measured with *EP* in Europe, Asia-Pacific, and MENA while in the other regions, the value effect exists in the regression specifications with a smaller number of index attributes. Differently, in Japan, the significant results of *TSKEW* and *ES* under all regression specifications they are included point out that skewness anomaly and profitability measured with earnings surprise are specific to Japan.

< Table 2.6 here >

The alternative version of index-level cross-sectional regression, presented in Table 2.6, uses the index attributes of *DY*, *StMom*, *ISKEW*, and *ROE* instead of *EP*, *IntMom*, *TSKEW*, and *OP* used in Table 2.5. The results of North America are similar with the ones in Table 2.5 for volatility measures. Differently, the momentum effect does not survive when estimation period of the momentum changes. In other words, short-term momentum (*StMom*) that covers the months from *t*-6 to *t*-2 reveals less information about future index returns than intermediate-term momentum (*IntMom*) that covers the months from *t*-12 to *t*-2. Moreover, change in the set of anomalies does not affect the significance of *BETA* and *MV*. On the other hand, while *TSKEW* is insignificant for all regression specifications in Table 2.5, *ISKEW* is almost persistently significant for all regression specifications that are run with fewer number of index attributes, except the one with *MIN*. Similar with *EP*, the alternative value measure of *DY* also provides some significant results when the regressions are run with either *MAX* or *MIN*. Furthermore, unlike *OP*, the alternative profitability measure of *ROE* is only significant when the regression is run with *MAX*. As a result, in North America, the volatility effect measured as *MAX* and *MIN*; beta, size, and value effects are still significant. In addition, in some cases, *ISKEW* provides significant power in the explanation of expected index returns.

In Panel B, the results of European country-industry indexes show that the total volatility measures and idiosyncratic volatility are still significant with high value of slope coefficient estimates. Moreover, the change in the measures of value, momentum, and skewness effects does not cause change in their results. The value measured as *DY*, the momentum measured as *StMom* have persistently significant coefficient estimates and the skewness measured as *ISKEW* provides significant coefficient estimates only when the regression is run with either *MAX* or *MIN*. In addition, the other value measure, *EBITDA/EV*, is still significant for all regression specifications, except the one with *MAX*. On the other hand, when the profitability is measured with *ROE* rather than *OP*, it provides persistently significant slope coefficient estimates. In conclusion, it can be inferred that in addition to volatility measures, *DY*, *StMom*, *ISKEW*, and *ROE* also have effects on expected returns of European country-industry indexes.

In Asia-Pacific country-industry indexes, the positive significant effects of total volatility measures of *Range*, *SD*, and idiosyncratic volatility, *IVOL*, still significantly exist. Moreover, *MAX* and *MIN* still have highly significant slope coefficient estimates in magnitude, which are positive for *MAX* and negative for *MIN*. The alternative measure of momentum effect, *StMom*, almost loses its effect on expected returns when it is measured with more recent past months, indicating that cumulative returns from months *t*-6 to *t*-2 have less information about expected returns. In addition, when the value effect is measured with *DY*, the value effect loses its persistent influence on index returns. The change in the measure of skewness does not cause change in the explanatory power of the skewness effect. Moreover, similar with Table 2.5, the effect of the index attributes of *BETA* and *MV* still exist. Differently, *EBITDA/EV* and *INV* provide only single evidence for their significance when the regression is run with *MIN*. These results indicate that in addition to significant index attributes presented in Table 2.5, *DY*, *ISKEW*, *EBITDA/EV* and *INV* also considerably affect country-industry index returns of Asia-Pacific countries.

In South America, the coefficient estimates of the all volatility measures increase notably for the first five regression specifications that are run with fewer number of anomalies compared to Table 2.5. On the other hand, when volatility measures are run with higher number of anomalies in the last five regression specifications, their coefficient estimates and the corresponding t-statistics sharply decrease. Moreover, the significant effects of *BETA* and *MV* are still valid. The value effect produces more power on expected index returns when the value effect is measured as *DY*. In addition, the effect of other value measure of *EBITDA/EV* also increases in some degree when it is included in the regression with the alternative measures set of Table 2.6. Unlike previous regions, measuring momentum effect with more recent past months (from *t*-6 to *t*-2) causes increase in the explanation power of the momentum effect. The skewness effect also still provides evidences for its validity even there is a decrease in the coefficient estimates in magnitude. According to these results, it can be concluded that different than Table 2.5, there is a notably significant value effect measured as *DY* and momentum effect measured as *StMom*.

In the region of MENA, the volatility measures are still significant and have nearly similar coefficient estimates with the ones in Table 2.5. Moreover, *BETA* and *MV* again have at least one significant coefficient estimates when the regression is run with either *MAX* or *MIN*. In addition, measuring value as *DY* rather than *EP* ratio decreases the number of significant coefficient estimates while measuring momentum as *StMom* rather than *IntMom* increases the number of significant coefficient estimates. On the other hand, the insignificant coefficient estimates of *ISKEW* point out that skewness measures do not affect expected index returns regardless of the measures of skewness. Similar with Table 2.5, the alternative regression results also show that volatility measures, *BETA*, value, and momentum effects have significant explanatory powers on the country-industry indexes of MENA.

Lastly, in Panel F of Table 2.6, the results of Japan are similar with the results of Table 2.5. The volatility measures persistently produce significant coefficient estimates. The results of the index attributes of *BETA*, *MV*, and *ES* provide evidences for the existence of significant effects on expected returns. Moreover, the measurement approach of value, momentum, skewness, and profitability do not cause change in the significance of the results in Table 2.5. In other words, there are persistent skewness and value effects in some regression specifications while momentum and profitability effects do not survive for all regression specifications. In conclusion, the results of Table 2.6 also support that there are significant effects of volatility measures, beta, value, skewness, and profitability (measured as *ES*) on future index returns.

As a summary, the results of the alternative regression in Table 2.6 are similar with Table 2.5 for volatility measures indicating that total volatility measures of *Range*, *SD*, *MAX*, *MIN*, and idiosyncratic volatility, *IVOL*, are persistently significant in all regression specifications for all regions, except North America. In North America, only *MAX* and *MIN* provide significant results. These results also point out that regional factors do not affect the significance of volatility measures. Moreover, when value measured as dividend yield, *DY*, produce persistently significant coefficient estimates in Europe, and at least one evidence for the significance of the coefficient estimates in all of other five regions. In addition, measuring momentum with more recent past data as in *StMom* causes considerably change in North America, Asia-Pacific, and South America. More specifically, in North America and Asia-Pacific the momentum effect sharply loses its explanatory power on expected returns. Inversely, in South America, measuring momentum with more recent past data increases significantly its explanatory power on future index returns. Furthermore, the results of both Tables 2.5 and 2.6 for all regions indicate that measuring skewness with different approaches does not reveal remarkable information about expected index returns. Moreover, the significances of profitability measures do not change regardless of the measurement approach for all regions, except Europe, where *ROE* persistently affects future expected returns in Table 2.6. As a result, it can be suggested the results of the regressions are not sensitive to the usage of either the alternative or fundamental definitions of these anomalies[10].

2.4. Conclusion

In this dissertation chapter, the cross-sectional relation between nineteen index attributes and expected index returns is examined based on the perspective of an international investor. Local industry indexes with 19 industries and 51 countries are taken into account as the international assets. The analyses are performed by dividing the country-industry indexes into six regions, which are North America, Europe, Asia-Pacific, South America, MENA (Middle East and North Africa), and Japan, to examine the significance of the anomalies across regions. Portfolio-level analyses are performed by using the regional versions of the asset-pricing models, which take into account the different characteristics of the regions and adjust returns to both global and regional risk factors that may change across regions. For each of nineteen index attributes, it is investigated that whether the quintile portfolios with different levels of attribute values generate different levels of returns. In addition to portfolio analyses, the cross-section of index returns is also examined by performing Fama-MacBeth cross-sectional regression analyses, which allow controlling the effects of several index attributes simultaneously.

The portfolio analyses and index-level cross-sectional regressions show that standard deviation, the widely used measure of total volatility, and the return range, the newly proposed proxy of total volatility in the previous chapter, have consistently significant

[10] As another alternative robustness check, panel regression analyses can be performed to increase the degree of freedom in the analyses. On the other hand, the estimation technique used for balanced panels also causes loss of observations.

effects on the returns of indexes from Europe, Asia-Pacific, South America, MENA, and Japan. In addition, the idiosyncratic volatility effect also significantly exists in these regions. On the other hand, the other total volatility measures of *MAX* and *MIN* strongly affect expected returns of all six regions, including North America. Since the country-industry indexes in North America are referred as the indexes having large market capitalization values, these results support the results of the previous chapter indicating that the effects of *Range*, *SD*, and *IVOL* are only existent for the returns of small-cap and in some cases medium-cap indexes while *MAX* and *MIN* effects strongly exist in any size of the indexes. Moreover, the trading strategies based on the size and value effects generate significant abnormal returns regardless of the region. However, the significance of the value effect changes depending on the measurement approach. In addition, for returns on the country-industry indexes of North America, Europe, and MENA, there is significant momentum effect, which is measured by using the past returns from either intermediate-term or short-term. Although the operating profitability as a measure of profitability is insignificant for all regions, the profitability effect either measured as earnings surprise or return on equity provides abnormal returns for Europe and Asia-Pacific. Both skewness measures, which are total and idiosyncratic skewness, have significant explanatory power on the returns of only European country-industry indexes.

The results of the index-level cross-sectional regressions show that the significant *IntMom* effect persistently exists in the regions of North America, Europe, and for some regression specifications in the regions of Asia-Pacific and MENA. On the other hand, when momentum is measured as *StMom*, there is a persistently momentum effect in the regions of Europe, MENA, and in some cases in South America. Moreover, all three measures of the value effect (*EP*, *DY*, and *EBITDA/EV*) have significant impact on future index returns in Europe while for the remaining regions the value effect's presence depends on the measurement approaches and regression specifications. In addition, the trading strategies based on measures of skewness generate significant abnormal returns consistently for Japan and in some regression specifications for South America, Asia-Pacific, and Europe. These results imply that measuring skewness with different approaches does not cause remarkable change in the results. For European country-industry indexes the profitability effect measured as *ES* and for Japan as *ROE* are consistently significant. These results also suggest that the significance of the profitability effect does not change depending on the different measurement approaches. Furthermore, the stand-alone measures of *INV* and *NSI* do not have significant effects on future index returns regardless of the region. Lastly, the usage of either the fundamental or alternative measures of the value, skewness, momentum, and profitability effects do not cause remarkable changes in the results.

The results of this dissertation chapter provide useful implications for the international investors, who aim to diversify their portfolios across regional country-industry indexes. The changing significance of the index attributes across regions can be due to region-specific stock market conditions, market regulations and economic activities. The profit opportunities, which arise by performing the trading strategies based on these index attributes, might be affected from the degree of market segmentation/integration. As regions become more integrated with the global market, some of the anomalies can lose its explanatory power on index returns or disappear over time.

2.5. Tables

Table 2.1. Regional Basic Statistics

This table shows the descriptive statistics of the nineteen index attributes for 19 industry indexes from 51 countries divided into six regions. The statistics are calculated by performing two steps method. In the first step, for each month in the sample period the cross-sectional averages of index attributes are calculated over the indexes. In the second step, the cross-sectional means are time-series averaged over the months. With the usage of these time-series data the standard deviation, maximum, and minimum of the cross-sectional means are calculated for every index attribute. Panels report the descriptive statistics for the regions of North America, Europe, Asia-Pacific, South America, MENA, and, Japan, respectively. *Range* is the return range within a month; *MAX* is the maximum daily return and *MIN* is the negative of the minimum daily return within a month; *SD* is the standard deviation of the returns; *IVOL* is the idiosyncratic volatility; *BETA* is the market beta from the ICAPM; *TSKEW* is the total skewness; *ISKEW* is the idiosyncratic skewness; *MV* is the market value in $US billions, *EP* is the earnings-to-price ratio, *DY* is the dividend yield, *EBITDA/EV* is the earnings before interest, taxes, depreciation, and amortization over enterprise value; *IntMom* is the intermediate-term momentum; *StMom* is the short-term momentum; *OP* is the operating profitability; *ES* is the earnings surprise; *ROE* is the return on equity; *INV* is the investments; and *NSI* is the net share issuance. The research period extends from January 1973 to July 2017, however, the start date changes across regions.

	North America				Europe				Asia-Pacific			
	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min
Range	0.0007	0.0028	0.0493	0.0001	0.0010	0.0039	0.0770	0.0001	0.0016	0.0084	0.1691	0.0002
MAX	0.0004	0.0014	0.0228	0.00003	0.0005	0.0025	0.0508	0.0001	0.0009	0.0056	0.1204	0.0001
MIN	0.0003	0.0014	0.0265	0.00002	0.0004	0.0015	0.0262	0.0001	0.0007	0.0030	0.0487	0.0001
SD	0.0008	0.0031	0.0533	0.0001	0.0010	0.0039	0.0743	0.0001	0.0016	0.0083	0.1645	0.0002
IVOL	0.0006	0.0025	0.0449	0.0001	0.0010	0.0036	0.0693	0.0001	0.0016	0.0080	0.1565	0.0002
BETA	0.0122	0.0456	0.6699	-0.0007	0.0068	0.0282	0.6270	-0.0910	0.0059	0.0416	0.9405	-0.1080
TSKEW	0.0009	0.0070	0.1201	-0.0143	0.0013	0.0162	0.3202	-0.0507	0.0018	0.0282	0.5634	-0.0275
ISKEW	0.0011	0.0064	0.1027	-0.0203	0.0011	0.0102	0.1846	-0.0492	0.0019	0.0230	0.4567	-0.0300

Table 2.1. Regional Basic Statistics (cont.)

	North America				Europe				Asia-Pacific			
	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min
MV	729.8432	900.2020	16686.0789	161.3723	43.6189	36.0451	464.7749	5.8354	25.1110	24.2985	153.5821	1.8564
EP	0.0009	0.0026	0.0443	0.0001	0.0011	0.0030	0.0533	0.0002	0.0010	0.0023	0.0401	0.0002
DY	0.0004	0.0013	0.0216	0.00004	0.0005	0.0014	0.0251	0.0001	0.0005	0.0013	0.0221	0.0001
EBITDA/EV	0.0027	0.0116	0.1955	-0.0002	0.0066	0.0341	0.5491	-0.0805	0.0030	0.0043	0.0356	-0.0001
IntMom	0.0005	0.0018	0.0103	-0.0131	0.0004	0.0008	0.0030	-0.0049	0.0003	0.0007	0.0028	-0.0029
StMom	0.0003	0.0015	0.0107	-0.0114	0.0002	0.0010	0.0119	-0.0048	0.0002	0.0005	0.0022	-0.0032
OP	0.0044	0.0202	0.3349	0.0003	0.0036	0.0120	0.1995	0.0002	0.0043	0.0163	0.2692	-0.0078
ES	0.0000	0.000001	0.000001	-0.00002	-0.0001	0.0026	0.0134	-0.0131	-0.0001	0.0010	0.0023	-0.0055
ROE	0.2215	0.9225	15.5907	0.0183	0.2748	1.0446	15.5500	-0.7867	0.4422	2.0150	32.2467	0.0310
INV	0.0082	0.0305	0.3459	-0.0001	0.0038	0.0051	0.0252	-0.0001	0.0054	0.0107	0.1734	0.0003
NSI	0.0018	0.0076	0.0971	-0.0008	0.0007	0.0024	0.0447	-0.0001	0.0011	0.0043	0.0829	-0.00005

Table 2.1. Regional Basic Statistics (cont.)

	South America				MENA				Japan			
	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min	Mean	Std. Dev.	Max	Min
Range	0.0033	0.0152	0.2510	0.0002	0.0021	0.0066	0.0867	0.0002	0.0010	0.0063	0.1322	0.0001
MAX	0.0017	0.0072	0.1056	0.0001	0.0011	0.0034	0.0479	0.0001	0.0005	0.0040	0.0892	0.00003
MIN	0.0016	0.0082	0.1454	0.0001	0.0010	0.0032	0.0388	0.0001	0.0004	0.0023	0.0431	0.00002
SD	0.0034	0.0151	0.2454	0.0002	0.0023	0.0076	0.1033	0.0002	0.0011	0.0065	0.1361	0.0001
IVOL	0.0033	0.0147	0.2375	0.0002	0.0023	0.0074	0.0996	0.0002	0.0009	0.0051	0.1015	0.0001
BETA	0.0073	0.0591	0.3670	-0.8134	0.0130	0.0801	1.1726	-0.1990	0.0121	0.1111	2.4597	-0.0586
TSKEW	0.0046	0.0294	0.2423	-0.2623	-0.0001	0.0231	0.2205	-0.1134	0.0026	0.0204	0.4387	-0.0862
ISKEW	0.0072	0.0310	0.3578	-0.1308	0.0005	0.0261	0.3122	-0.1147	0.0029	0.0090	0.1929	-0.0191
MV	82.7960	36.1613	209.0000	19.5515	59.3342	92.3070	1241.7500	12.7057	480.9292	399.0396	6908.9474	125.8156
EP	0.0037	0.0118	0.1121	0.0002	0.0020	0.0038	0.0507	0.0004	0.0006	0.0028	0.0504	0.00005
DY	0.0021	0.0134	0.2135	0.0001	0.0007	0.0011	0.0159	0.0002	0.0002	0.0010	0.0181	0.00002
EBITDA/EV	0.0098	0.0358	0.4505	-0.0003	0.0034	0.0034	0.0454	-0.0002	0.0035	0.0170	0.2870	-0.00003
IntMom	0.0003	0.0007	0.0030	-0.0011	0.0001	0.0003	0.0015	-0.0009	0.0007	0.0025	0.0088	-0.0161
StMom	0.0002	0.0004	0.0023	-0.0011	0.0001	0.0002	0.0010	-0.0009	0.0004	0.0023	0.0157	-0.0169
OP	0.0047	0.0163	0.2328	-0.0009	0.0061	0.0126	0.1641	0.0009	0.0029	0.0156	0.2592	-0.0041
ES	0.3433	2.1082	19.2936	-0.0033	-0.00001	0.0001	0.0005	-0.0003	0.00003	0.0002	0.0022	-0.0002
ROE	0.3291	0.8142	6.6800	-0.3995	0.3685	0.5662	7.4100	0.0058	0.1210	0.5940	10.0641	-0.1828
INV	0.0059	0.0199	0.1495	-0.1050	0.0115	0.0173	0.2132	0.0002	0.0018	0.0039	0.0534	-0.0004
NSI	0.0005	0.0064	0.0101	-0.0853	0.0034	0.0245	0.3838	-0.0005	0.0004	0.0019	0.0342	-0.0001

Table 2.2. Regional Correlation Matrix

This table presents the correlation analyses between the nineteen index attributes for the regions of North America, Europe, Asia-Pacific, South America, MENA, and Japan, respectively. Correlation analyses are calculated by performing two steps method. In the first step, every month in the research period cross-correlations among the index attributes across indexes are calculated. Then, the cross-correlations are time-series averaged over the months in the research period.

Panel A: North America

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.8560	1																	
MIN	0.8348	0.4636	1																
SD	0.9546	0.8229	0.7954	1															
IVOL	0.8851	0.7690	0.7289	0.9213	1														
BETA	0.5215	0.4505	0.4575	0.5589	0.2856	1													
TSKEW	0.0578	0.0561	0.0391	0.0632	0.0673	0.0110	1												
ISKEW	0.0439	0.0428	0.0285	0.0503	0.0446	0.0311	0.8313	1											
MV	-0.1528	-0.1501	-0.1153	-0.1499	-0.2546	0.1529	-0.0339	-0.0140	1										
EP	-0.1021	-0.0843	-0.0858	-0.1154	-0.0959	-0.0817	-0.0931	-0.0872	-0.0851	1									
DY	-0.2632	-0.2247	-0.2244	-0.2894	-0.2390	-0.2286	-0.0690	-0.0832	-0.0470	0.3699	1								
EBITDA /EV	-0.0167	-0.0250	-0.0028	-0.0187	0.0085	-0.0638	-0.0582	-0.0403	-0.1648	0.2847	0.1208	1							
IntMom	0.0341	0.0195	0.0201	0.0401	0.0108	0.0967	0.0696	0.1082	0.0695	-0.1042	-0.1533	-0.0618	1						
StMom	0.0058	-0.0159	0.0109	0.0112	-0.0159	0.0678	0.0892	0.1218	0.0536	-0.1439	-0.1324	-0.0377	0.6168	1					
OP	-0.0961	-0.0985	-0.0699	-0.0979	-0.1139	0.0024	-0.0684	-0.0645	0.2176	0.1005	0.0048	0.0567	-0.0087	0.0012	1				
ES	0.0172	0.0058	0.0194	0.0173	0.0071	0.0193	-0.0032	-0.0100	0.0209	0.0195	-0.0698	0.0084	0.2230	0.1531	-0.0659	1			
ROE	-0.0915	-0.0941	-0.0696	-0.0977	-0.1177	0.0075	-0.0658	-0.0551	0.2276	0.2532	-0.0681	0.1653	0.1329	0.0666	0.4099	0.0402	1		
INV	0.0868	0.0767	0.0697	0.0854	0.0892	0.0289	0.0410	0.0605	-0.1356	-0.0478	-0.0500	-0.0719	-0.0073	-0.0032	-0.0245	-0.0582	-0.0727	1	
NSI	0.0300	0.0228	0.0330	0.0294	0.0285	0.0119	-0.0263	-0.0172	-0.1318	-0.0503	0.0339	0.0007	0.0566	-0.0022	-0.1072	0.0544	-0.0932	0.0187	1

Table 2.2. Regional Correlation Matrix (cont.)

Panel B: Europe

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.8712	1																	
MIN	0.8373	0.4752	1																
SD	0.9596	0.8402	0.8003	1															
IVOL	0.9190	0.8076	0.7643	0.9491	1														
BETA	0.3272	0.2803	0.2834	0.3690	0.1478	1													
TSKEW	0.0605	0.0611	0.0433	0.0620	0.0709	-0.0220	1												
ISKEW	0.0416	0.0434	0.0291	0.0429	0.0483	-0.0166	0.8848	1											
MV	-0.2821	-0.2547	-0.2320	-0.2736	-0.3708	0.2078	-0.0824	-0.0619	1										
EP	0.0416	0.0361	0.0357	0.0432	0.0451	0.0001	-0.0426	-0.0501	-0.0537	1									
DY	-0.0054	-0.0119	0.0026	-0.0100	-0.0029	-0.0320	-0.0922	-0.1101	0.0390	0.3281	1								
EBITDA /EV	0.0582	0.0529	0.0479	0.0617	0.0743	-0.0347	-0.0251	-0.0297	-0.0976	0.1844	0.0981	1							
IntMom	0.0085	0.0136	0.0031	0.0114	0.0135	-0.0077	0.1586	0.1787	0.0089	-0.1228	-0.1470	-0.0089	1						
StMom	-0.0045	0.0009	-0.0087	-0.0044	-0.0017	-0.0176	0.1489	0.1669	0.0154	-0.1301	-0.1329	-0.0014	0.6257	1					
OP	0.0358	0.0317	0.0332	0.0373	0.0387	0.0103	0.0102	0.0027	0.0784	0.0685	0.0720	0.0390	0.0102	0.0144	1				
ES	0.0041	0.0039	0.0028	0.0005	-0.0006	-0.0064	0.0047	0.0085	-0.0139	-0.0166	-0.0169	-0.0223	0.0832	0.0635	-0.0004	1			
ROE	-0.0095	-0.0074	-0.0073	-0.0123	-0.0030	-0.0261	-0.0193	-0.0220	0.0355	0.1247	0.0615	0.0832	0.1151	0.0698	0.3572	0.0182	1		
INV	-0.0024	-0.0056	0.0027	-0.0017	0.0051	-0.0012	-0.0069	-0.0068	-0.0131	-0.0050	-0.0349	-0.0451	-0.0010	0.0034	0.0803	-0.0180	0.0145	1	
NSI	0.0109	0.0072	0.0119	0.0143	0.0093	0.0264	-0.0105	-0.0142	0.0114	-0.0069	-0.0591	-0.0527	-0.0138	-0.0126	-0.0203	-0.0049	-0.0540	0.0142	1

Table 2.2. Regional Correlation Matrix (cont.)

Panel C: Asia-Pacific

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.9044	1																	
MIN	0.8743	0.6020	1																
SD	0.9541	0.8652	0.8357	1															
IVOL	0.9374	0.8558	0.8161	0.9803	1														
BETA	0.2588	0.2138	0.2534	0.2838	0.1601	1													
TSKEW	0.1364	0.1394	0.1017	0.1328	0.1425	-0.0168	1												
ISKEW	0.1098	0.1148	0.0799	0.1046	0.1111	-0.0112	0.9434	1											
MV	-0.1703	-0.1708	-0.1272	-0.1601	-0.1901	0.1474	-0.1310	-0.1048	1										
EP	0.0221	0.0259	0.0194	0.0246	0.0237	-0.0220	-0.0807	-0.0769	-0.0313	1									
DY	-0.1187	-0.1112	-0.1016	-0.1287	-0.1258	-0.0666	-0.1571	-0.1677	-0.1175	0.3718	1								
EBITDA /EV	0.0591	0.0490	0.0615	0.0675	0.0676	-0.0089	-0.0108	0.0010	-0.0772	0.3034	0.1441	1							
IntMom	0.0149	0.0153	0.0054	0.0207	0.0223	-0.0018	0.1390	0.1550	-0.0140	-0.1115	-0.1429	-0.0393	1						
StMom	0.0186	0.0098	0.0199	0.0241	0.0263	-0.0047	0.1411	0.1530	-0.0048	-0.1203	-0.1266	-0.0062	0.6205	1					
OP	-0.0282	-0.0262	-0.0324	-0.0363	-0.0349	-0.0299	0.0147	0.0126	-0.0329	0.0336	0.0857	0.1172	-0.0016	-0.0027	1				
ES	0.0121	0.0095	0.0127	0.0249	0.0259	0.0123	0.0023	0.0083	0.0209	0.0166	-0.0294	0.0183	0.1025	0.0923	-0.0104	1			
ROE	-0.0365	-0.0298	-0.0430	-0.0439	-0.0438	-0.0230	0.0097	0.0171	-0.0289	0.0988	0.0816	0.1027	0.1004	0.0593	0.5550	0.0202	1		
INV	0.0446	0.0379	0.0423	0.0475	0.0473	0.0182	0.0190	0.0090	0.0112	-0.0210	-0.0731	-0.0598	-0.0397	-0.0264	0.0019	0.0250	-0.0100	1	
NSI	0.0365	0.0292	0.0361	0.0413	0.0439	0.0067	-0.0174	-0.0128	0.0365	-0.0149	-0.0402	-0.0340	0.0338	0.0099	-0.0163	-0.0143	-0.0280	0.0239	1

Table 2.2. Regional Correlation Matrix (cont.)

Panel D: South America

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.8412	1																	
MIN	0.8139	0.4161	1																
SD	0.9415	0.8097	0.7592	1															
IVOL	0.8969	0.7796	0.7158	0.9438	1														
BETA	0.4073	0.3596	0.3405	0.4668	0.2478	1													
TSKEW	0.0402	0.0458	0.0057	0.0424	0.0415	0.0257	1												
ISKEW	0.0444	0.0504	0.0077	0.0483	0.0431	0.0370	0.9137	1											
MV	-0.0617	-0.0641	-0.0413	-0.0325	-0.1437	0.3129	-0.0516	-0.0327	1										
EP	0.1033	0.0856	0.1005	0.1221	0.1204	0.0309	-0.0301	-0.0314	0.0011	1									
DY	0.0397	0.0207	0.0493	0.0380	0.0612	-0.0578	-0.1181	-0.1128	-0.0086	0.3208	1								
EBITDA /EV	0.1325	0.1190	0.1040	0.1521	0.1525	0.0596	0.0142	0.0279	-0.0219	0.3463	0.0458	1							
IntMom	0.0435	0.0299	0.0336	0.0376	0.0258	0.0684	0.1024	0.1265	0.0461	-0.0609	-0.1241	0.0135	1						
StMom	0.0346	0.0341	0.0174	0.0294	0.0127	0.0682	0.0963	0.1163	0.0511	-0.0779	-0.1263	0.0397	0.6032	1					
OP	0.0353	0.0333	0.0339	0.0310	-0.0030	0.0813	-0.0220	-0.0274	0.1706	0.0584	0.0528	0.1630	0.0257	0.0289	1				
ES	-0.0100	-0.0123	-0.0197	-0.0123	-0.0038	-0.0149	0.0296	0.0175	-0.0121	-0.0095	0.0184	-0.0439	0.0688	0.0403	-0.0383	1			
ROE	0.0170	0.0169	0.0135	0.0126	-0.0084	0.0649	-0.0324	-0.0347	0.1644	0.1890	0.0712	0.2034	0.1410	0.0927	0.4483	0.0112	1		
INV	0.0243	0.0095	0.0363	0.0344	0.0219	0.0415	-0.0334	-0.0457	0.0450	0.0264	0.0583	-0.0774	-0.0092	-0.0077	0.0147	-0.0001	-0.0049	1	
NSI	-0.0194	-0.0137	-0.0183	-0.0149	-0.0289	0.0336	-0.0253	-0.0302	0.0390	-0.0195	-0.0907	-0.0575	0.0323	0.0207	-0.0719	-0.0158	-0.0669	0.0561	1

Table 2.2. Regional Correlation Matrix (cont.)

Panel E: MENA

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.7423	1																	
MIN	0.7289	0.3775	1																
SD	0.8387	0.7238	0.6679	1															
IVOL	0.8203	0.7065	0.6537	0.8683	1														
BETA	0.1952	0.1849	0.1568	0.2361	0.1356	1													
TSKEW	0.1163	0.1174	0.0817	0.1170	0.1210	0.0346	1												
ISKEW	0.1163	0.1166	0.0813	0.1189	0.1202	0.0433	0.8699	1											
MV	-0.0794	-0.0615	-0.0599	-0.0541	-0.0789	0.1214	-0.0071	0.0037	1										
EP	-0.0315	-0.0144	-0.0314	-0.0323	-0.0425	0.0279	-0.0986	-0.0895	0.0353	1									
DY	-0.0859	-0.0857	-0.0648	-0.0978	-0.1013	-0.0144	-0.1697	-0.1688	-0.1519	0.4361	1								
EBITDA /EV	-0.0106	-0.0069	-0.0153	-0.0246	-0.0199	-0.0646	-0.0797	-0.0687	-0.1473	0.2707	0.2974	1							
IntMom	0.0593	0.0810	0.0310	0.0670	0.0576	0.0035	0.2205	0.2168	0.0598	-0.1094	-0.1337	-0.0525	1						
StMom	0.0646	0.0815	0.0402	0.0625	0.0557	-0.0101	0.1671	0.1562	0.0333	-0.1026	-0.1019	-0.0380	0.5612	1					
OP	0.0235	0.0109	0.0285	0.0186	0.0142	0.0225	0.0078	0.0235	0.0097	-0.0148	0.1169	0.0231	0.0642	0.0509	1				
ES	0.0502	0.0410	0.0418	0.0554	0.0528	0.0302	-0.0054	-0.0138	0.0000	0.0452	0.0152	0.0448	0.0594	0.0158	-0.1066	1			
ROE	-0.0020	0.0054	-0.0108	-0.0221	-0.0079	-0.0441	0.0629	0.0708	-0.0076	0.1010	0.1342	0.1387	0.1120	0.0924	0.3444	0.0044	1		
INV	-0.0538	-0.0548	-0.0334	-0.0433	-0.0418	-0.0416	-0.0486	-0.0439	0.0761	0.0326	-0.0424	-0.0189	-0.0330	-0.0174	0.0257	-0.0668	-0.0354	1	
NSI	0.0211	0.0036	0.0290	0.0260	0.0386	-0.0004	-0.0218	-0.0409	-0.0259	-0.0987	-0.0895	-0.0643	-0.0355	-0.0611	-0.0779	-0.0021	0.0082	0.0292	1

Table 2.2. Regional Correlation Matrix (cont.)

Panel F: Japan

	Range	*MAX*	*MIN*	*SD*	*IVOL*	*BETA*	*TSKEW*	*ISKEW*	*MV*	*EP*	*DY*	*EBITDA /EV*	*IntMom*	*StMom*	*OP*	*ES*	*ROE*	*INV*	*NSI*
Range	1																		
MAX	0.8654	1																	
MIN	0.7895	0.4199	1																
SD	0.9154	0.7874	0.7355	1															
IVOL	0.8637	0.7507	0.6936	0.9347	1														
BETA	0.5081	0.4324	0.4216	0.5679	0.3539	1													
TSKEW	0.1941	0.1782	0.1505	0.2191	0.2141	0.1109	1												
ISKEW	0.1280	0.1173	0.0998	0.1512	0.1486	0.0712	0.8039	1											
MV	-0.1241	-0.1024	-0.1080	-0.1321	-0.2009	0.0882	-0.0090	-0.0392	1										
EP	-0.0908	-0.0690	-0.0836	-0.1033	-0.0786	-0.0748	0.0378	0.0211	-0.0306	1									
DY	-0.0374	-0.0191	-0.0499	-0.0446	-0.0373	-0.0677	0.0316	0.0149	-0.0651	0.3137	1								
EBITDA /EV	-0.1382	-0.1153	-0.1174	-0.1477	-0.1492	-0.0806	-0.0760	-0.0662	0.1809	0.1924	0.2219	1							
IntMom	-0.0354	-0.0438	-0.0178	-0.0372	-0.0278	-0.0417	-0.1534	-0.0994	0.0995	-0.1426	-0.1558	0.0018	1						
StMom	-0.0297	-0.0387	-0.0094	-0.0302	-0.0245	-0.0262	-0.0602	-0.0166	0.0663	-0.1466	-0.1270	0.0037	0.5691	1					
OP	-0.0740	-0.0657	-0.0656	-0.0811	-0.0829	-0.0290	-0.0649	-0.0756	0.1587	0.1496	0.2113	0.2031	-0.0100	0.0140	1				
ES	-0.0123	-0.0039	-0.0184	-0.0109	-0.0160	-0.0030	-0.0590	-0.0503	0.0176	-0.0671	-0.1146	-0.0144	0.3460	0.2122	-0.1646	1			
ROE	-0.1281	-0.1199	-0.0908	-0.1410	-0.1354	-0.0606	-0.1132	-0.0928	0.1971	0.4347	0.0363	0.2567	0.1269	0.0276	0.1661	0.0292	1		
INV	0.0838	0.0675	0.0810	0.0866	0.0966	0.0336	0.0765	0.0404	-0.0846	0.0525	-0.0820	-0.0050	-0.0493	-0.0300	0.1485	-0.0380	0.1347	1	
NSI	0.0064	0.0100	-0.0026	0.0047	0.0030	-0.0090	0.0007	0.0174	0.0468	-0.0523	-0.1607	-0.0373	0.0824	0.0477	-0.0116	0.0233	0.0433	0.0524	1

Table 2.3. Equal-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions

For every month in the sample period, quintile portfolios are formed by sorting the country-industry indexes based on nineteen index attributes over the past one month. Portfolio 1 (5) includes the indexes with the lowest (highest) values for the relevant index attribute. The table reports the equal-weighted average raw (R_{Raw}) and risk-adjusted returns (alphas) for the 5- 1*Attribute* portfolios, which long the portfolio with the highest variable and thereafter, short the one with the lowest variable. The Jensen alphas for the 5-1*Attribute* portfolios are estimated using the regional versions of the ICAPM, the Fama-French 3-Factor Model, and Fama-French-Carhart 4-Factor Model, which are denoted as α_{ICAPM}, α_{FF3}, and α_{FFC4}, respectively. Panels report the results for the regions of North America, Europe, Asia-Pacific, South America, MENA, and Japan, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

	North America				Europe			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	0.0016	0.0016	0.0003	0.0006	0.0161***	0.0135***	0.0045*	0.0047**
	(0.63)	(0.94)	(0.18)	(0.31)	(4.39)	(5.06)	(1.93)	(2.06)
5-1*MAX*	0.0304***	0.0300***	0.0287***	0.0292***	0.0629***	0.0605***	0.0524***	0.0522***
	(12.40)	(16.23)	(15.49)	(15.25)	(17.26)	(22.27)	(20.76)	(21.22)
5-1*MIN*	-0.0305***	-0.0309***	-0.0321***	-0.0319***	-0.0422***	-0.0440***	-0.0508***	-0.0503***
	(-13.04)	(-17.87)	(-18.39)	(-17.20)	(-14.56)	(-19.58)	(-24.67)	(-24.00)
5-1*SD*	0.0019	0.0019	0.0005	0.0007	0.0188***	0.0159***	0.0064***	0.0067***
	(0.69)	(1.06)	(0.28)	(0.36)	(4.83)	(5.68)	(2.64)	(2.85)
5-1*IVOL*	0.0029	0.0034*	0.0009	0.0012	0.0184***	0.0161***	0.0062***	0.0065***
	(1.17)	(1.80)	(0.49)	(0.62)	(4.96)	(5.84)	(2.68)	(2.89)
5-1*BETA*	-0.0001	-0.0015	-0.0006	-0.0004	-0.0032	-0.0068***	-0.0055**	-0.0051**
	(-0.05)	(-0.81)	(-0.36)	(-0.22)	(-1.28)	(-3.06)	(-2.42)	(-2.14)
5-1*TSKEW*	-0.00001	-0.0005	-0.0007	-0.0002	0.0032**	0.0034**	0.0026*	0.0024*
	(-0.01)	(-0.34)	(-0.43)	(-0.15)	(2.28)	(2.47)	(1.90)	(1.77)
5-1*ISKEW*	0.0012	0.0012	0.0015	0.0017	0.0036**	0.0037***	0.0030**	0.0025**
	(0.92)	(0.84)	(0.95)	(1.08)	(2.53)	(2.77)	(2.32)	(1.96)
5-1*MV*	-0.0033*	-0.0050***	-0.0053***	-0.0049**	-0.0069***	-0.0087***	-0.0089***	-0.0090***
	(-1.76)	(-2.67)	(-2.80)	(-2.53)	(-3.76)	(-5.45)	(-5.28)	(-5.19)
5-1*EP*	0.0038**	0.0043**	0.0040**	0.0040**	0.0077***	0.0071***	0.0052***	0.0058***
	(2.19)	(2.46)	(2.20)	(2.23)	(4.17)	(3.69)	(2.89)	(3.61)
5-1*DY*	0.0012	0.0014	0.0016	0.0016	0.0072***	0.0072***	0.0065***	0.0074***
	(0.63)	(0.80)	(0.95)	(0.95)	(3.61)	(3.68)	(4.20)	(5.06)
5-1*EBITDA*	0.0007	0.0007	0.0005	0.0002	0.0079***	0.0082***	0.0058***	0.0055***
/EV	(0.39)	(0.44)	(0.33)	(0.15)	(7.19)	(7.01)	(5.11)	(4.80)
5-1*IntMom*	0.0047**	0.0057***	0.0066***	0.0066***	0.0093***	0.0106***	0.0109***	0.0109***
	(2.18)	(2.71)	(3.31)	(3.31)	(3.45)	(4.19)	(4.42)	(4.42)
5-1*StMom*	-0.0003	0.0006	0.0007	-0.0019	0.0081***	0.0096***	0.0103***	0.0071***
	(-0.13)	(0.29)	(0.34)	(-1.00)	(3.34)	(4.09)	(4.29)	(3.15)
5-1*OP*	-0.0010	-0.0011	-0.000001	-0.0003	0.0007	0.0002	0.0004	0.0003
	(-0.69)	(-0.76)	(-0.0004)	(-0.18)	(0.50)	(0.17)	(0.28)	(0.20)
5-1*ES*	-0.0020	-0.0019	-0.0022	-0.0031*	0.0027*	0.0030**	0.0023*	0.0020
	(-1.18)	(-1.06)	(-1.03)	(-1.65)	(1.85)	(2.24)	(1.73)	(1.56)
5-1*ROE*	-0.0009	-0.0010	0.0008	0.0003	0.0059***	0.0061***	0.0057***	0.0050***
	(-0.57)	(-0.56)	(0.40)	(0.19)	(3.79)	(4.03)	(3.37)	(3.18)
5-1*INV*	-0.0005	-0.0004	0.0009	0.0011	-0.0023	-0.0025*	-0.0017	-0.0015
	(-0.30)	(-0.24)	(0.48)	(0.59)	(-1.58)	(-1.79)	(-1.32)	(-1.17)
5-1*NSI*	-0.0035**	-0.0037***	-0.0036**	-0.0036**	-0.0024**	-0.0028***	-0.0023**	-0.0021*
	(-2.50)	(-2.68)	(-2.39)	(-2.42)	(-2.09)	(-2.59)	(-2.10)	(-1.81)

Table 2.3. Equal-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions (cont.)

	Asia-Pacific				South America			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	0.0206***	0.0176***	0.0107***	0.0114***	0.0384***	0.0326***	0.0163**	0.0158**
	(5.08)	(4.78)	(3.14)	(3.29)	(3.00)	(3.07)	(2.45)	(2.47)
5-1*MAX*	0.0755***	0.0728***	0.0652***	0.0665***	0.0854***	0.0814***	0.0654***	0.0654***
	(18.19)	(19.60)	(20.13)	(19.58)	(8.13)	(9.21)	(11.38)	(11.54)
5-1*MIN*	-0.0465***	-0.0486***	-0.0514***	-0.0516***	-0.0432***	-0.0474***	-0.0565***	-0.0567***
	(-12.16)	(-14.74)	(-17.36)	(-17.58)	(-3.72)	(-4.45)	(-8.40)	(-8.79)
5-1*SD*	0.0237***	0.0202***	0.0126***	0.0134***	0.0439***	0.0381***	0.0210***	0.0207***
	(5.39)	(5.09)	(3.44)	(3.59)	(3.49)	(3.63)	(2.98)	(3.06)
5-1*IVOL*	0.0233***	0.0202***	0.0126***	0.0134***	0.0439***	0.0384***	0.0215***	0.0211***
	(5.51)	(5.23)	(3.65)	(3.81)	(3.46)	(3.65)	(3.06)	(3.12)
5-1*BETA*	-0.0040	-0.0063*	-0.0089***	-0.0080**	0.0022	-0.0004	-0.0039	-0.0028
	(-1.13)	(-1.92)	(-2.65)	(-2.34)	(0.20)	(-0.04)	(-0.61)	(-0.45)
5-1*TSKEW*	0.0022	0.0022	0.0016	0.0014	-0.0015	-0.0016	-0.0018	-0.0012
	(0.98)	(0.99)	(0.62)	(0.48)	(-0.31)	(-0.31)	(-0.45)	(-0.31)
5-1*ISKEW*	0.0027	0.0025	0.0019	0.0017	-0.0001	-0.0001	0.0011	0.0011
	(1.17)	(1.07)	(0.70)	(0.58)	(-0.01)	(-0.02)	(0.27)	(0.28)
5-1*MV*	-0.0136***	-0.0144***	-0.0141***	-0.0147***	-0.0319**	-0.0329***	-0.0234**	-0.0227**
	(-6.04)	(-6.08)	(-6.01)	(-6.73)	(-2.53)	(-2.92)	(-2.36)	(-2.36)
5-1*EP*	0.0083***	0.0091***	0.0105***	0.0097***	-0.0002	0.0009	0.0046	0.0049
	(2.89)	(3.09)	(3.51)	(3.25)	(-0.02)	(0.11)	(0.83)	(0.93)
5-1*DY*	0.0081***	0.0090***	0.0096***	0.0106***	0.0096**	0.0100**	0.0109***	0.0110***
	(3.02)	(3.39)	(4.46)	(5.19)	(2.24)	(2.52)	(2.82)	(2.91)
5-1*EBITDA*	0.0081***	0.0081***	0.0081***	0.0082***	0.0165*	0.0146*	0.0128**	0.0121**
/EV	(3.14)	(2.94)	(3.27)	(3.24)	(1.75)	(1.78)	(2.35)	(2.26)
5-1*IntMom*	-0.0003	0.0001	0.0030***	0.0030	-0.0070	-0.0066	0.0002	0.0002
	(-0.09)	(0.02)	(0.75)	(0.75)	(-0.65)	(-0.68)	(0.03)	(0.03)
5-1*StMom*	-0.0010	-0.0004	-0.0004	-0.0042	-0.0028	-0.0023	0.0068	0.0050
	(-0.28)	(-0.11)	(-0.11)	(-1.48)	(-0.31)	(-0.29)	(1.46)	(1.17)
5-1*OP*	0.0019	0.0031	0.0037	0.0031	-0.0123	-0.0121	-0.0052	-0.0045
	(0.61)	(0.97)	(1.05)	(0.87)	(-1.17)	(-1.28)	(-0.69)	(-0.62)
5-1*ES*	0.0045**	0.0046**	0.0029	0.0022	-0.0010	-0.0016	-0.0003	0.0005
	(2.11)	(2.22)	(1.18)	(0.80)	(-0.28)	(-0.46)	(-0.07)	(0.12)
5-1*ROE*	0.0026	0.0035	0.0046***	0.0035	0.0006	0.0002	0.0035	0.0027
	(1.12)	(1.47)	(1.79)	(1.38)	(0.09)	(0.03)	(0.64)	(0.51)
5-1*INV*	-0.0026	-0.0028	-0.0045*	-0.0043*	-0.0190*	-0.0190**	-0.0152**	-0.0144**
	(-1.21)	(-1.23)	(-1.92)	(-1.84)	(-1.78)	(-2.02)	(-2.23)	(-2.17)
5-1*NSI*	-0.0020	-0.0029	-0.0032*	-0.0033*	0.0008	0.0005	-0.0005	0.0003
	(-1.14)	(-1.69)	(-1.73)	(-1.77)	(0.19)	(0.10)	(-0.11)	(0.08)

Table 2.3. Equal-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions (cont.)

	MENA				Japan			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	0.0047	-0.0013	-0.0051	-0.0030	0.0111***	0.0110***	0.0113***	0.0105***
	(0.74)	(-0.26)	(-0.97)	(-0.63)	(3.63)	(4.65)	(4.50)	(4.24)
5-1*MAX*	0.0628***	0.0567***	0.0512***	0.0525***	0.0315***	0.0314***	0.0309***	0.0294***
	(10.78)	(12.23)	(11.05)	(11.55)	(10.38)	(12.45)	(11.66)	(11.82)
5-1*MIN*	-0.0628***	-0.0673***	-0.0691***	-0.0670***	-0.0199***	-0.0203***	-0.0194***	-0.0196***
	(-9.53)	(-13.87)	(-14.32)	(-14.19)	(-7.17)	(-8.38)	(-7.32)	(-6.93)
5-1*SD*	0.0107*	0.0037	0.0002	0.0025	0.0137***	0.0135***	0.0137***	0.0123***
	(1.69)	(0.78)	(0.05)	(0.53)	(4.28)	(5.39)	(5.42)	(4.90)
5-1*IVOL*	0.0108*	0.0040	-0.0002	0.0019	0.0143***	0.0141***	0.0140***	0.0126***
	(1.67)	(0.82)	(-0.04)	(0.42)	(4.64)	(5.80)	(5.78)	(5.17)
5-1*BETA*	-0.0015	-0.0043	-0.0042	-0.0036	0.0013	0.0005	0.0014	0.0002
	(-0.33)	(-1.00)	(-0.89)	(-0.80)	(0.47)	(0.21)	(0.60)	(0.06)
5-1*TSKEW*	0.0076**	0.0072**	0.0059	0.0073*	-0.0013	-0.0013	-0.0016	-0.0013
	(1.98)	(2.03)	(1.51)	(1.93)	(-0.58)	(-0.59)	(-0.76)	(-0.62)
5-1*ISKEW*	0.0074*	0.0069*	0.0064*	0.0080**	0.0001	0.0002	0.0001	0.0002
	(1.85)	(1.91)	(1.67)	(2.16)	(0.06)	(0.07)	(0.06)	(0.11)
5-1*MV*	-0.0127***	-0.0152***	-0.0155***	-0.0160***	-0.0057***	-0.0063***	-0.0060***	-0.0068***
	(-3.60)	(-4.35)	(-4.29)	(-4.44)	(-2.56)	(-2.97)	(-2.82)	(-3.18)
5-1*EP*	0.0082***	0.0088***	0.0065**	0.0072**	0.0028	0.0023	0.0019	0.0029
	(2.68)	(2.63)	(2.04)	(2.40)	(1.24)	(1.09)	(0.90)	(1.39)
5-1*DY*	0.0140***	0.0153***	0.0147***	0.0147***	0.0038	0.0040	0.0038*	0.0044*
	(4.06)	(4.30)	(4.49)	(4.67)	(1.32)	(1.43)	(1.65)	(1.95)
5-1*EBITDA*	0.0091**	0.0104***	0.0099***	0.0096***	0.0015	0.0008	0.0007	0.0006
/EV	(2.20)	(2.65)	(2.79)	(2.72)	(0.67)	(0.38)	(0.34)	(0.26)
5-1*IntMom*	0.0086*	0.0089**	0.0064	0.0064	-0.0003	0.0002	-0.0003	-0.0003
	(1.82)	(1.99)	(1.49)	(1.49)	(-0.12)	(0.05)	(-0.10)	(-0.10)
5-1*StMom*	0.0110**	0.0117***	0.0103***	0.0100***	0.0011	0.0015	0.0009	-0.0012
	(2.52)	(3.02)	(2.90)	(2.99)	(0.45)	(0.59)	(0.34)	(-0.53)
5-1*OP*	0.0040	0.0030	0.0007	0.0007	0.0001	-0.0007	-0.0009	-0.0007
	(1.15)	(0.77)	(0.17)	(0.16)	(0.06)	(-0.34)	(-0.49)	(-0.38)
5-1*ES*	-0.0031	-0.0032	-0.0012	-0.0012	0.0002	-0.0004	-0.0005	-0.0011
	(-0.72)	(-0.79)	(-0.30)	(-0.31)	(0.08)	(-0.16)	(-0.22)	(-0.47)
5-1*ROE*	0.0047	0.0059	0.0079**	0.0075**	-0.0008	-0.0009	-0.0004	-0.0004
	(1.28)	(1.57)	(2.14)	(1.99)	(-0.39)	(-0.41)	(-0.22)	(-0.24)
5-1*INV*	-0.0051	-0.0052	-0.0073	-0.0066	0.0024	0.0008	-0.0008	-0.0010
	(-1.14)	(-1.10)	(-1.48)	(-1.32)	(1.00)	(0.36)	(-0.39)	(-0.50)
5-1*NSI*	-0.0061*	-0.0070**	-0.0047*	-0.0046	0.0011	0.0013	0.0006	-0.0001
	(-1.78)	(-2.28)	(-1.67)	(-1.64)	(0.62)	(0.66)	(0.30)	(-0.03)

Table 2.4. Value-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions

For every month in the sample period, quintile portfolios are formed by sorting the country-industry indexes based on nineteen index attributes over the past one month. Portfolio 1 (5) includes the indexes with the lowest (highest) values for the relevant index attribute. The table reports the value-weighted average raw (R_{Raw}) and risk-adjusted returns (alphas) for the 5- 1*Attribute* portfolios, which long the portfolio with the highest variable and thereafter, short the one with the lowest variable. The Jensen alphas for the 5-1*Attribute* portfolios are estimated using the regional versions of the ICAPM, the Fama-French 3-Factor Model, and Fama-French-Carhart 4-Factor Model, which are denoted as α_{ICAPM}, α_{FF3}, and α_{FFC4}, respectively. Panels report the results for the regions of North America, Europe, Asia-Pacific, South America, MENA, and Japan, respectively. The Newey-West (1987) adjusted t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

	North America				Europe			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	-0.0051**	-0.0054**	-0.0056**	-0.0058**	0.0077**	0.0048	-0.0004	-0.0004
	(-1.98)	(-2.54)	(-2.41)	(-2.46)	(1.99)	(1.53)	(-0.13)	(-0.14)
5-1*MAX*	0.0223***	0.0214***	0.0209***	0.0211***	0.0490***	0.0460***	0.0409***	0.0408***
	(8.33)	(9.68)	(8.91)	(8.68)	(12.75)	(14.89)	(13.08)	(13.60)
5-1*MIN*	-0.0314***	-0.0321***	-0.0321***	-0.0321***	-0.0447***	-0.0469***	-0.0509***	-0.0505***
	(-12.92)	(-15.62)	(-14.79)	(-14.00)	(-14.03)	(-17.73)	(-20.03)	(-19.61)
5-1*SD*	-0.0046*	-0.0045**	-0.0048**	-0.0045**	0.0092**	0.0061*	0.0008	0.0009
	(-1.68)	(-2.11)	(-2.07)	(-1.93)	(2.20)	(1.91)	(0.25)	(0.29)
5-1*IVOL*	-0.0006	-0.0004	-0.0019	-0.0012	0.0088**	0.0063*	0.0006	0.0006
	(-0.22)	(-0.21)	(-0.82)	(-0.50)	(2.17)	(1.94)	(0.19)	(0.19)
5-1*BETA*	-0.0023	-0.0040*	-0.0035	-0.0031	-0.0033	-0.0061***	-0.0051**	-0.0049**
	(-0.91)	(-1.85)	(-1.58)	(-1.37)	(-1.34)	(-2.79)	(-2.25)	(-2.10)
5-1*TSKEW*	-0.0007	-0.0015	-0.0002	0.0008	0.0001	-0.00002	0.0006	0.0009
	(-0.42)	(-0.82)	(-0.13)	(0.48)	(0.08)	(-0.01)	(0.34)	(0.46)
5-1*ISKEW*	-0.0021	-0.0023	-0.0006	-0.0001	0.0002	0.0002	0.0015	0.0008
	(-1.14)	(-1.16)	(-0.27)	(-0.04)	(0.12)	(0.12)	(0.82)	(0.47)
5-1*MV*	-0.0031*	-0.0046**	-0.0048***	-0.0044**	-0.0063***	-0.0078***	-0.0080***	-0.0082***
	(-1.65)	(-2.55)	(-2.59)	(-2.39)	(-3.05)	(-4.71)	(-4.64)	(-4.70)
5-1*EP*	0.0026	0.0032***	0.0028	0.0031	0.0051**	0.0045**	0.0030	0.0040**
	(1.35)	(1.65)	(1.36)	(1.50)	(2.25)	(1.96)	(1.41)	(2.11)
5-1*DY*	0.0005	0.00004	-0.0017	-0.0015	0.0062**	0.0059**	0.0058***	0.0072***
	(0.20)	(0.002)	(-0.83)	(-0.70)	(2.51)	(2.44)	(3.27)	(4.24)
5-1*EBITDA*	0.0017	0.0021	0.0005	-0.000004	0.0035	0.0043	0.0030	0.0025
/EV	(0.84)	(0.99)	(0.24)	(-0.002)	(2.28)	(2.96)	(2.07)	(1.75)
5-1*IntMom*	0.0035	0.0042*	0.0046**	0.0046**	0.0068***	0.0083***	0.0093***	0.0093***
	(1.45)	(1.73)	(1.97)	(1.97)	(2.58)	(3.49)	(3.81)	(3.81)
5-1*StMom*	-0.0001	0.0010	0.0014	-0.0015	0.0027	0.0045**	0.0058**	0.0019
	(-0.06)	(0.43)	(0.57)	(-0.75)	(1.12)	(1.97)	(2.25)	(0.85)
5-1*OP*	0.0022	0.0024	0.0029	0.0022	-0.0005	-0.0003	0.0005	0.0003
	(1.32)	(1.46)	(1.50)	(1.26)	(-0.34)	(-0.19)	(0.32)	(0.21)
5-1*ES*	-0.0004	0.0003	0.0010	-0.0004	0.0027	0.0033	0.0024	0.0017
	(-0.20)	(0.16)	(0.42)	(-0.19)	(1.56)	(2.02)	(1.37)	(1.02)
5-1*ROE*	0.0001	-0.0001	0.0015	0.0010	0.0038	0.0045	0.0055	0.0044
	(0.03)	(-0.05)	(0.63)	(0.44)	(2.02)	(2.64)	(3.03)	(2.61)
5-1*INV*	0.00002	0.0001	0.0012	0.0012	-0.0019	-0.0022	-0.0009	-0.0007
	(0.01)	(0.07)	(0.65)	(0.63)	(-1.17)	(-1.30)	(-0.57)	(-0.44)
5-1*NSI*	-0.0041**	-0.0041	-0.0031	-0.0036	-0.0035	-0.0045	-0.0048	-0.0043
	(-2.03)	(-2.11)	(-1.47)	(-1.68)	(-2.36)	(-3.10)	(-3.05)	(-2.69)

Table 2.4. Value-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions (cont.)

	Asia-Pacific				South America			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	0.0079*	0.0051	0.0009	0.0025	0.0124	0.0077	0.0001	0.0004
	(1.85)	(1.16)	(0.19)	(0.54)	(1.37)	(1.03)	(0.02)	(0.08)
5-1*MAX*	0.0564***	0.0535***	0.0481***	0.0497***	0.0669***	0.0632***	0.0509***	0.0509***
	(12.56)	(12.12)	(10.79)	(10.90)	(7.24)	(7.92)	(9.01)	(9.06)
5-1*MIN*	-0.0522***	-0.0547***	-0.0561***	-0.0562***	-0.0463***	-0.0499***	-0.0515***	-0.0512***
	(-13.41)	(-15.63)	(-15.77)	(-15.81)	(-5.87)	(-6.86)	(-9.49)	(-9.73)
5-1*SD*	0.0101**	0.0066	0.0011	0.0027	0.0196**	0.0146*	0.0061	0.0064
	(2.18)	(1.42)	(0.23)	(0.56)	(2.02)	(1.84)	(0.99)	(1.06)
5-1*IVOL*	0.0108**	0.0076	0.0018	0.0035	0.0207**	0.0162*	0.0095	0.0096
	(2.37)	(1.63)	(0.38)	(0.72)	(2.06)	(1.95)	(1.40)	(1.43)
5-1*BETA*	-0.0076*	-0.0100**	-0.0113**	-0.0107**	0.0052	0.0014	-0.0040	-0.0036
	(-1.83)	(-2.48)	(-2.51)	(-2.26)	(0.79)	(0.21)	(-0.67)	(-0.61)
5-1*TSKEW*	-0.0006	-0.0005	-0.0011	-0.0008	-0.0036	-0.0039	-0.0014	-0.0014
	(-0.19)	(-0.16)	(-0.34)	(-0.24)	(-0.62)	(-0.61)	(-0.32)	(-0.31)
5-1*ISKEW*	-0.0015	-0.0017	-0.0032	-0.0032	-0.0017	-0.0019	0.0008	0.0008
	(-0.50)	(-0.56)	(-0.95)	(-0.87)	(-0.31)	(-0.31)	(0.18)	(0.18)
5-1*MV*	-0.0131***	-0.0138***	-0.0134***	-0.0143***	-0.0207**	-0.0225***	-0.0118***	-0.0119***
	(-5.55)	(-5.54)	(-5.37)	(-6.24)	(-2.20)	(-2.56)	(-2.75)	(-2.78)
5-1*EP*	0.0082**	0.0088**	0.0115***	0.0109***	0.0033	0.0020	0.0011	0.0018
	(2.19)	(2.29)	(2.92)	(2.70)	(0.83)	(0.50)	(0.24)	(0.40)
5-1*DY*	0.0093***	0.0101***	0.0096***	0.0113***	0.0087**	0.0084**	0.0071*	0.0074**
	(2.76)	(2.82)	(3.35)	(3.92)	(2.35)	(2.31)	(1.95)	(2.01)
5-1*EBITDA*	0.0063*	0.0055	0.0048	0.0052	0.0050	0.0041	0.0057	0.0057
/EV	(1.83)	(1.58)	(1.29)	(1.36)	(1.63)	(1.20)	(1.51)	(1.49)
5-1*IntMom*	-0.0013	-0.0006	0.0012	0.0012	0.0038	0.0031	0.0072	0.0072
	(-0.34)	(-0.15)	(0.26)	(0.26)	(0.58)	(0.43)	(1.21)	(1.21)
5-1*StMom*	-0.0038	-0.0034	-0.0033	-0.0082**	-0.0056	-0.0051	0.0061	0.0034
	(-1.03)	(-0.90)	(-0.77)	(-2.40)	(-0.59)	(-0.60)	(1.19)	(0.72)
5-1*OP*	0.0003	0.0012	0.0027	0.0025	0.0025	0.0019	0.0030	0.0029
	(0.07)	(0.33)	(0.73)	(0.65)	(0.56)	(0.39)	(0.55)	(0.58)
5-1*ES*	0.0035	0.0038*	0.0023	0.0007	-0.0019	-0.0024	-0.0001	0.0006
	(1.59)	(1.68)	(0.81)	(0.24)	(-0.49)	(-0.61)	(-0.01)	(0.14)
5-1*ROE*	0.0015	0.0016	0.0015	0.0009	-0.0004	-0.0003	0.0020	0.0010
	(0.61)	(0.62)	(0.51)	(0.32)	(-0.07)	(-0.05)	(0.46)	(0.24)
5-1*INV*	-0.0008	-0.0014	-0.0025	-0.0024	-0.0028	-0.0034	-0.0044	-0.0044
	(-0.36)	(-0.56)	(-0.96)	(-0.90)	(-0.48)	(-0.61)	(-0.74)	(-0.77)
5-1*NSI*	-0.0026	-0.0035	-0.0024	-0.0023	0.0017	0.0015	0.0026	0.0034
	(-1.27)	(-1.57)	(-1.05)	(-0.96)	(0.43)	(0.36)	(0.59)	(0.81)

Table 2.4. Value-Weighted Returns on 5-1*Attribute* Portfolios from Six Regions (cont.)

	MENA				Japan			
	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}	R_{Raw}	α_{ICAPM}	α_{FF3}	α_{FFC4}
5-1*Range*	-0.0031	-0.0099*	-0.0113**	-0.0095*	0.0097***	0.0095***	0.0097***	0.0092***
	(-0.43)	(-1.72)	(-2.02)	(-1.79)	(2.87)	(3.64)	(3.82)	(3.58)
5-1*MAX*	0.0597***	0.0528***	0.0486***	0.0505***	0.0288***	0.0286***	0.0282***	0.0268***
	(8.56)	(9.82)	(8.23)	(9.08)	(8.76)	(10.98)	(10.34)	(10.06)
5-1*MIN*	-0.0681***	-0.0723***	-0.0730***	-0.0712***	-0.0191***	-0.0195***	-0.0189***	-0.0193***
	(-10.93)	(-14.11)	(-14.16)	(-14.01)	(-7.02)	(-7.93)	(-7.76)	(-7.64)
5-1*SD*	0.0062	-0.0013	-0.0021	0.0005	0.0127***	0.0123***	0.0129***	0.0120***
	(0.80)	(-0.22)	(-0.38)	(0.09)	(3.55)	(4.82)	(5.00)	(4.56)
5-1*IVOL*	0.0052	-0.0025	-0.0044	-0.0018	0.0122***	0.0118***	0.0121***	0.0111***
	(0.63)	(-0.41)	(-0.76)	(-0.34)	(3.44)	(4.61)	(4.58)	(4.10)
5-1*BETA*	0.0012	-0.0014	-0.0007	0.00005	0.0021	0.0011	0.0024	0.0010
	(0.24)	(-0.30)	(-0.16)	(0.01)	(0.68)	(0.39)	(0.89)	(0.36)
5-1*TSKEW*	0.0076	0.0067	0.0039	0.0049	-0.0021	-0.0022	-0.0019	-0.0016
	(1.48)	(1.44)	(0.81)	(1.10)	(-0.89)	(-0.91)	(-0.81)	(-0.69)
5-1*ISKEW*	0.0063	0.0055	0.0035	0.0047	0.0003	0.0002	0.0004	0.0004
	(1.24)	(1.22)	(0.73)	(1.08)	(0.11)	(0.06)	(0.15)	(0.16)
5-1*MV*	-0.0072*	-0.0094**	-0.0091**	-0.0093**	-0.0048**	-0.0054***	-0.0051***	-0.0059***
	(-1.93)	(-2.53)	(-2.35)	(-2.41)	(-2.34)	(-2.70)	(-2.57)	(-2.97)
5-1*EP*	0.0033	0.0030	0.0006	0.0007	0.0023	0.0019	0.0016	0.0030
	(0.87)	(0.84)	(0.16)	(0.18)	(0.94)	(0.80)	(0.61)	(1.21)
5-1*DY*	0.0081*	0.0084*	0.0068*	0.0054	0.0043	0.0047*	0.0028	0.0033
	(1.70)	(1.93)	(1.82)	(1.48)	(1.47)	(1.65)	(1.26)	(1.47)
5-1*EBITDA*	0.0023	0.0021	0.0015	0.0009	0.0040*	0.0037*	0.0044*	0.0040*
/EV	(0.53)	(0.57)	(0.42)	(0.25)	(1.77)	(1.68)	(1.91)	(1.75)
5-1*IntMom*	0.0087	0.0079	0.0051	0.0051	-0.0002	0.0001	-0.0005	-0.0005
	(1.52)	(1.51)	(0.99)	(0.99)	(-0.06)	(0.02)	(-0.15)	(-0.15)
5-1*StMom*	0.0088**	0.0086**	0.0061	0.0061	0.0010	0.0011	0.0010	-0.0008
	(2.18)	(2.16)	(1.59)	(1.67)	(0.35)	(0.39)	(0.33)	(-0.30)
5-1*OP*	0.0020	0.0008	-0.0015	-0.0013	0.0002	-0.0007	-0.0009	-0.0007
	(0.50)	(0.19)	(-0.32)	(-0.28)	(0.10)	(-0.30)	(-0.45)	(-0.34)
5-1*ES*	-0.0017	-0.0010	0.0004	0.0004	0.00004	-0.0008	-0.0009	-0.0016
	(-0.36)	(-0.22)	(0.09)	(0.10)	(0.01)	(-0.29)	(-0.34)	(-0.65)
5-1*ROE*	0.0056	0.0050	0.0072*	0.0076*	-0.0006	-0.0012	-0.0004	-0.0005
	(1.31)	(1.25)	(1.77)	(1.84)	(-0.28)	(-0.51)	(-0.19)	(-0.28)
5-1*INV*	-0.0070*	-0.0061	-0.0072	-0.0066	0.0011	-0.0005	-0.0009	-0.0011
	(-1.69)	(-1.42)	(-1.47)	(-1.35)	(0.45)	(-0.19)	(-0.35)	(-0.42)
5-1*NSI*	-0.0057*	-0.0060*	-0.0045	-0.0044	0.0014	0.0013	0.0002	-0.0005
	(-1.65)	(-1.81)	(-1.35)	(-1.29)	(0.61)	(0.59)	(0.07)	(-0.21)

Table 2.5. Cross-Sectional Regressions for Regions

For each month in the sample period, the return of the country-industry indexes is regressed on the previous month's the return range within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return (*MAX*), the negative of the minimum daily return (*MIN*), the market beta (*BETA*), the natural logarithm of the market capitalization value (*MV*), the earnings-to-price ratio (*EP*), the intermediate-term momentum (*IntMom*), the total skewness (*TSKEW*), the earnings before interest, taxes, depreciation, and amortization over enterprise value (*EBITDA/EV*), the earnings surprise (*ES*), the net share issuance (*NSI*), the operating profitability (*OP*), and the investments (*INV*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *OP*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. Panel A to F report the results for the portfolios from North America, Europe, Asia-Pacific, South America, MENA, and Japan, respectively. The time-series averages of the slope coefficients and R-square values are reported in the table. The Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: North America

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
-0.0185					0.0034*	-0.0007	-0.0009**	0.0255	0.0147***						0.4171
(-0.41)					(1.67)	(-0.64)	(-2.23)	(1.45)	(3.67)						
	0.0138				0.0034	-0.0004	-0.0007*	0.0262	0.0146***						0.4208
	(0.27)				(1.51)	(-0.33)	(-1.74)	(1.48)	(3.60)						
		0.0211			0.0013	-0.0006	-0.0007*	0.0260	0.0142***						0.4177
		(0.48)			(0.77)	(-0.62)	(-1.85)	(1.51)	(3.53)						
			1.3197***		-0.0142***	-0.0013	0.0019***	0.0624***	0.0184***						0.4494
			(20.02)		(-6.59)	(-1.06)	(4.98)	(3.68)	(4.88)						
				-1.5533***	0.0180***	-0.0003	-0.0031***	-0.0114	0.0098**						0.4658
				(-25.19)	(9.61)	(-0.29)	(-7.58)	(-0.60)	(2.25)						
0.0142					0.0002	-0.0004	0.0003	0.0391	0.0172***	-0.0034	-0.0037	-10.4090	-0.0016	0.0025	0.5772
(0.25)					(0.07)	(-0.29)	(0.63)	(1.26)	(3.49)	(-0.31)	(-0.80)	(-1.12)	(-0.63)	(0.39)	
	0.0354				0.0005	-0.0005	0.0004	0.0325	0.0172***	-0.0021	-0.0041	-11.2886	-0.0027	0.0032	0.5790
	(0.58)				(0.16)	(-0.35)	(0.85)	(1.06)	(3.51)	(-0.18)	(-0.92)	(-1.20)	(-1.07)	(0.50)	
		0.0370			-0.0007	-0.0004	0.0004	0.0332	0.0170***	-0.0021	-0.0043	-12.7421	-0.0029	0.0035	0.5780
		(0.70)			(-0.30)	(-0.28)	(0.83)	(1.08)	(3.46)	(-0.19)	(-0.96)	(-1.35)	(-1.12)	(0.55)	
			1.3201***		-0.0176***	-0.0003	0.0019***	0.0914***	0.0203***	-0.0020	0.0018	-12.8853	-0.0054*	0.0087	0.5994
			(16.97)		(-6.49)	(-0.23)	(4.36)	(3.24)	(4.19)	(-0.17)	(0.37)	(-1.34)	(-2.20)	(1.34)	
				-1.5753***	0.0181***	-0.0005	-0.0014***	-0.0220	0.0129***	0.0035	-0.0071	-8.3448	0.0030	-0.0094	0.6146
				(-19.44)	(7.19)	(-0.39)	(-2.79)	(-0.73)	(2.61)	(0.37)	(-1.48)	(-0.90)	(1.09)	(-1.62)	

Table 2.5. Cross-Sectional Regressions for Regions (cont.)

Panel B: Europe															
Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1678***					-0.0015	-0.0006	0.0002	0.0314***	0.0143***						0.2041
(5.26)					(-1.02)	(-1.34)	(0.80)	(4.03)	(6.22)						
	0.2296***				-0.0020	-0.0007	0.0006**	0.0287***	0.0146***						0.2164
	(5.98)				(-1.31)	(-1.49)	(2.00)	(3.66)	(6.61)						
		0.2294***			-0.0016	-0.0007	0.0006**	0.0282***	0.0146***						0.2161
		(6.08)			(-1.15)	(-1.47)	(2.02)	(3.61)	(6.67)						
			1.1928***		-0.0104***	-0.0018***	0.0036***	0.0190***	0.0148***						0.2757
			(23.41)		(-6.59)	(-3.78)	(12.68)	(2.19)	(5.57)						
				-1.0201***	0.0076***	0.0002	-0.0042***	0.0525***	0.0118***						0.2444
				(-24.81)	(5.07)	(0.44)	(-12.83)	(6.15)	(4.32)						
0.1184***					-0.0016	-0.0006	-0.0003	0.0380***	0.0137***	0.0107**	0.0001	0.3479	-0.0003	-0.0010	0.2300
(3.37)					(-0.90)	(-1.01)	(-0.68)	(3.16)	(5.41)	(2.25)	(0.02)	(0.77)	(-0.35)	(-0.47)	
	0.1519***				-0.0020	-0.0008	0.00005	0.0402***	0.0137***	0.0097**	-0.0008	0.3916	-0.0003	-0.0009	0.2398
	(3.56)				(-1.05)	(-1.33)	(0.12)	(3.47)	(5.58)	(2.02)	(-0.35)	(0.84)	(-0.34)	(-0.42)	
		0.1547***			-0.0026	-0.0008	0.0001	0.0408***	0.0137***	0.0098**	-0.0008	0.3783	-0.0004	-0.0008	0.2390
		(3.78)			(-1.55)	(-1.29)	(0.19)	(3.53)	(5.62)	(2.02)	(-0.35)	(0.79)	(-0.38)	(-0.37)	
			1.2888***		-0.0152***	-0.0020***	0.0036***	0.0367***	0.0140***	0.0042	-0.0039*	0.2346	0.0006	-0.0022	0.2992
			(23.35)		(-7.71)	(-2.93)	(9.45)	(2.68)	(4.90)	(0.88)	(-1.95)	(0.46)	(0.64)	(-1.31)	
				-1.2283***	0.0120***	0.0001	-0.0045***	0.0290**	0.0119***	0.0195***	0.0056**	0.4465	-0.0009	0.0004	0.2812
				(-24.49)	(6.34)	(0.11)	(-11.23)	(2.14)	(4.47)	(4.20)	(1.98)	(1.00)	(-0.86)	(0.18)	

Table 2.5. Cross-Sectional Regressions for Regions (cont.)

Panel C: Asia-Pacific															
Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1784***					-0.0024	-0.0003	-0.0009**	0.0649***	0.0034						0.2748
(5.46)					(-1.56)	(-0.31)	(-2.01)	(3.46)	(0.84)						
	0.2413***				-0.0029*	-0.0006	-0.0006	0.0654***	0.0038						0.2833
	(6.36)				(-1.92)	(-0.73)	(-1.35)	(3.53)	(0.96)						
		0.2387***			-0.0024	-0.0006	-0.0006	0.0655***	0.0039						0.2832
		(6.37)			(-1.60)	(-0.69)	(-1.35)	(3.56)	(0.99)						
			0.9846***		-0.0084***	-0.0021**	0.0011***	0.0510***	0.0042						0.3160
			(17.38)		(-5.34)	(-2.41)	(2.63)	(2.79)	(1.16)						
				-0.7556***	0.0057***	0.0019**	-0.0036***	0.0713***	0.0047						0.2909
				(-16.70)	(3.77)	(2.08)	(-8.73)	(4.00)	(1.12)						
0.1143***					-0.0041**	-0.0002	-0.0002	0.0500**	0.0111***	-0.0004	-0.0035	14.8144	-0.0005	0.0017	0.3322
(3.44)					(-2.24)	(-0.23)	(-0.30)	(2.12)	(3.16)	(-0.04)	(-0.73)	(1.00)	(-0.20)	(0.31)	
	0.1364***				-0.0043**	-0.0003	0.00002	0.0518**	0.0119***	-0.0043	-0.0035	12.5235	0.0005	0.0027	0.3366
	(3.68)				(-2.37)	(-0.31)	(0.04)	(2.28)	(3.54)	(-0.41)	(-0.73)	(0.80)	(0.25)	(0.51)	
		0.1375***			-0.0048***	-0.0002	-0.00001	0.0499**	0.0117***	-0.0045	-0.0036	12.9455	0.0006	0.0027	0.3362
		(3.73)			(-2.78)	(-0.21)	(-0.01)	(2.18)	(3.52)	(-0.44)	(-0.76)	(0.82)	(0.31)	(0.50)	
			0.9764***		-0.0126***	-0.0028***	0.0019***	0.0399	0.0124***	0.0003	-0.0011	18.6313	-0.0019	-0.0017	0.3712
			(17.45)		(-6.82)	(-2.80)	(3.71)	(1.59)	(3.60)	(0.03)	(-0.27)	(1.39)	(-1.06)	(-0.32)	
				-0.8756***	0.0047**	0.0021**	-0.0027***	0.0500*	0.0096***	0.0048	-0.0053	7.5070	0.0007	0.0065	0.3614
				(-13.58)	(2.33)	(2.06)	(-4.77)	(1.84)	(2.67)	(0.39)	(-1.14)	(0.63)	(0.30)	(1.22)	

Table 2.5. Cross-Sectional Regressions for Regions (cont.)

Panel D: South America

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.4181***					0.0045	-0.0091	-0.0041	0.0086	0.0004						0.3593
(2.99)					(0.71)	(-1.26)	(-1.03)	(0.14)	(0.06)						
	0.5215***				0.0041	-0.0105	-0.0039	-0.0021	0.0009						0.3736
	(2.97)				(0.64)	(-1.29)	(-0.97)	(-0.03)	(0.11)						
		0.5348***			0.0078	-0.0104	-0.0036	0.0019	0.0010						0.3731
		(2.70)			(1.06)	(-1.28)	(-0.95)	(0.03)	(0.13)						
			1.3395***		-0.0106***	-0.0088*	-0.0012	-0.0079	-0.0005						0.4185
			(12.76)		(-2.94)	(-1.73)	(-0.27)	(-0.12)	(-0.05)						
				-0.5658	0.0177***	-0.0131	-0.0072**	0.0273	0.0047						0.3758
				(-1.36)	(2.58)	(-1.15)	(-2.39)	(0.69)	(1.03)						
0.2216***					-0.0036	-0.0023	-0.0006	0.0345	0.0032	0.0355	-0.0014	-0.1198	0.0021	0.0117*	0.5327
(2.94)					(-1.05)	(-1.47)	(-0.56)	(1.45)	(0.57)	(1.56)	(-0.15)	(-0.28)	(0.55)	(1.70)	
	0.3129***				-0.0068*	-0.0027*	-0.0001	0.0336	0.0045	0.0249	0.0026	-0.2940	0.0032	0.0057	0.5405
	(3.30)				(-1.76)	(-1.77)	(-0.09)	(1.34)	(0.82)	(1.20)	(0.25)	(-0.57)	(0.82)	(0.85)	
		0.2846***			-0.0024	-0.0027*	0.0001	0.0311	0.0042	0.0221	0.0032	-0.2094	0.0030	0.0068	0.5399
		(3.25)			(-0.76)	(-1.83)	(0.05)	(1.25)	(0.77)	(1.08)	(0.30)	(-0.44)	(0.78)	(1.01)	
			1.5627***		-0.0164***	-0.0054***	0.0022***	0.0068	0.0056	0.0123	-0.0069	0.2439	0.0005	0.0127	0.5707
			(13.19)		(-4.62)	(-3.16)	(2.57)	(0.31)	(0.98)	(0.79)	(-0.86)	(0.65)	(0.13)	(1.64)	
				-1.3550***	0.0176***	-0.0014	-0.0037***	0.0513**	0.0031	0.0649**	-0.0038	-0.2594	0.0008	-0.0050	0.5575
				(-13.84)	(5.45)	(-0.89)	(-3.44)	(2.11)	(0.48)	(2.43)	(-0.46)	(-0.67)	(0.19)	(-0.68)	

Table 2.5. Cross-Sectional Regressions for Regions (cont.)

Panel E: MENA

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.1368**					0.0012	0.0001	-0.0012	0.0795***	0.0114***						0.3045
(2.32)					(0.42)	(0.10)	(-1.53)	(4.32)	(2.71)						
	0.1906***				0.0010	0.0004	-0.0011	0.0806***	0.0126***						0.3159
	(3.15)				(0.32)	(0.36)	(-1.50)	(4.33)	(3.12)						
		0.1867***			0.0012	0.0004	-0.0011	0.0820***	0.0125***						0.3159
		(3.05)			(0.38)	(0.41)	(-1.46)	(4.41)	(3.11)						
			1.2507***		-0.0071***	-0.0006	0.0010	0.0745***	0.0137***						0.3612
			(13.44)		(-2.66)	(-0.64)	(1.29)	(3.18)	(3.27)						
				-1.0375***	0.0067**	0.0006	-0.0040***	0.0742***	0.0066						0.3458
				(-10.57)	(2.18)	(0.66)	(-5.45)	(4.49)	(1.30)						
0.0455					0.0030	-0.0016	-0.0004	0.0781**	0.0083	0.0059	-0.0019	-0.0560	0.0084	-0.0002	0.4652
(0.35)					(0.65)	(-0.47)	(-0.38)	(2.37)	(1.25)	(0.35)	(-0.24)	(-0.10)	(1.45)	(-0.02)	
	0.3144**				0.0001	-0.0014	0.0007	0.0663**	0.0065	-0.0031	-0.0005	0.0330	0.0086	-0.0062	0.4760
	(1.97)				(0.02)	(-0.46)	(0.56)	(2.06)	(0.91)	(-0.19)	(-0.06)	(0.06)	(1.38)	(-0.81)	
		0.2154**			0.0026	-0.0017	0.0003	0.0691**	0.0070	0.0021	-0.0021	0.0356	0.0087	-0.0043	0.4737
		(2.06)			(0.62)	(-0.56)	(0.32)	(2.14)	(0.99)	(0.13)	(-0.27)	(0.07)	(1.40)	(-0.54)	
			1.5243***		-0.0079**	-0.0057	0.0016**	0.0827**	0.0043	-0.0100	-0.0006	0.2563	0.0072	-0.0038	0.5076
			(9.50)		(-2.08)	(-1.71)	(2.49)	(2.35)	(0.61)	(-0.68)	(-0.09)	(0.56)	(1.32)	(-0.49)	
				-1.1633***	0.0086**	-0.0003	-0.0026**	0.0468	0.0051	0.0166	0.0013	0.2808	0.0054	0.0043	0.4895
				(-9.31)	(2.05)	(-0.09)	(-2.31)	(1.53)	(0.69)	(1.01)	(0.17)	(0.54)	(0.97)	(0.47)	

Table 2.5. Cross-Sectional Regressions for Regions (cont.)

Panel F: Japan															
Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*TSKEW*	*MV*	*EP*	*IntMom*	*EBITDA /EV*	*OP*	*ES*	*INV*	*NSI*	R^2
0.2532***					-0.0010	-0.0107***	-0.0010	0.1977**	0.0032						0.5592
(3.88)					(-0.42)	(-5.00)	(-1.40)	(2.49)	(0.54)						
	0.4128***				-0.0026	-0.0120***	0.0002	0.2682***	0.0032						0.5607
	(5.28)				(-0.94)	(-5.19)	(0.25)	(3.13)	(0.56)						
		0.3506***			0.0015	-0.0119***	0.0002	0.2664***	0.0033						0.5593
		(5.23)			(0.67)	(-5.12)	(0.27)	(3.08)	(0.58)						
			1.1069***		-0.0098***	-0.0146***	0.0007	0.2062***	0.0040						0.5775
			(13.15)		(-3.47)	(-6.46)	(1.09)	(2.61)	(0.65)						
				-1.3049***	0.0141***	-0.0034	-0.0039***	0.0817	0.0030						0.5675
				(-11.82)	(5.67)	(-1.58)	(-5.35)	(1.24)	(0.49)						
0.0649					-0.0028	-0.0120***	-0.0014	0.0304	-0.0096	0.0275	0.0318	0.6686*	0.0200	-0.0544	0.8148
(0.55)					(-0.59)	(-2.72)	(-1.07)	(0.15)	(-0.92)	(0.79)	(1.31)	(1.90)	(1.05)	(-1.61)	
	0.2910**				-0.0049	-0.0137***	-0.0004	0.0643	-0.0088	0.0244	0.0279	0.7159**	0.0155	-0.0427	0.8169
	(2.10)				(-0.86)	(-3.21)	(-0.33)	(0.31)	(-0.78)	(0.75)	(1.26)	(2.35)	(0.76)	(-1.35)	
		0.2122*			-0.0004	-0.0139***	-0.0004	0.0841	-0.0087	0.0218	0.0235	0.7173**	0.0129	-0.0437	0.8168
		(1.81)			(-0.08)	(-3.27)	(-0.36)	(0.39)	(-0.78)	(0.67)	(1.04)	(2.39)	(0.63)	(-1.39)	
			0.8315***		-0.0085*	-0.0113***	0.0008	0.0609	-0.0056	0.0196	0.0078	0.8926*	0.0034	-0.0607*	0.8198
			(5.29)		(-1.76)	(-2.68)	(0.81)	(0.35)	(-0.57)	(0.50)	(0.37)	(1.77)	(0.22)	(-1.73)	
				-1.4720***	0.0130***	-0.0052	-0.0039***	-0.0356	-0.0116	0.0404	0.0253	1.0665***	0.0181	-0.0358	0.8222
				(-8.59)	(3.00)	(-1.24)	(-3.26)	(-0.22)	(-0.96)	(1.28)	(1.00)	(2.57)	(1.02)	(-0.84)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions

For each month in the sample period, the return of the country-industry indexes is regressed on the previous month's the return range within a month (*Range*), the standard deviation (*SD*), the idiosyncratic volatility (*IVOL*), the maximum daily return (*MAX*), the negative of the minimum daily return (*MIN*), the market beta (*BETA*), the natural logarithm of the market capitalization value (*MV*), the dividend yield (*DY*), the short-term momentum (*StMom*), the idiosyncratic skewness (*ISKEW*), the earnings before interest, taxes, depreciation, and depreciation over enterprise value (*EBITDA/EV*), the earnings surprise (*ES*), the net share issuance (*NSI*), the return on equity (*ROE*), and the investments (*INV*). All variables are as explained before. In the calculation of the anomalies of *EBITDA/EV*, *ES*, *NSI*, *ROE*, and *INV*, the start date of data changes depending on the availability. Therefore, for the last five regression specifications that include these anomalies the research period starts in June 1983. Panel A to F report the results for the portfolios from North America, Europe, Asia-Pacific, South America, MENA, and Japan, respectively. The time-series averages of the slope coefficients and R-square values are reported in the table. The Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: North America

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.0066					0.0019	-0.0015*	-0.0009**	0.0286	0.0069						0.3988
(0.15)					(0.92)	(-1.89)	(-2.31)	(0.87)	(1.15)						
	0.0324				0.0017	-0.0017**	-0.0007*	0.0350	0.0060						0.4015
	(0.65)				(0.77)	(-2.07)	(-1.79)	(1.05)	(1.01)						
		0.0287			0.0010	-0.0017**	-0.0007*	0.0349	0.0057						0.3997
		(0.66)			(0.55)	(-2.13)	(-1.93)	(1.06)	(0.95)						
			1.3406***		-0.0128***	-0.0016**	0.0014***	0.1486***	0.0118*						0.4370
			(21.88)		(-5.48)	(-1.96)	(3.81)	(4.62)	(1.78)						
				-1.5634***	0.0169***	-0.0013	-0.0029***	-0.0958***	0.0009						0.4506
				(-25.57)	(9.47)	(-1.49)	(-8.00)	(-2.93)	(0.14)						
-0.0372					0.0012	-0.0007	-0.0002	-0.0349	0.0054	0.0018	-2.9866	0.0001	0.0010	0.0057	0.5688
(-0.64)					(0.40)	(-0.75)	(-0.39)	(-0.79)	(0.65)	(0.18)	(-0.40)	(1.42)	(0.36)	(1.01)	
	-0.0255				0.0012	-0.0008	-0.0001	-0.0349	0.0045	0.0041	-4.1507	0.0001	-0.0002	0.0072	0.5705
	(-0.40)				(0.39)	(-0.87)	(-0.23)	(-0.78)	(0.55)	(0.41)	(-0.57)	(1.28)	(-0.06)	(1.32)	
		-0.0137			-0.0002	-0.0008	-0.0001	-0.0323	0.0037	0.0032	-4.5634	0.0001	-0.0001	0.0075	0.5697
		(-0.26)			(-0.07)	(-0.80)	(-0.26)	(-0.72)	(0.46)	(0.32)	(-0.62)	(1.37)	(-0.03)	(1.36)	
			1.3931***		-0.0161***	-0.0008	0.0015***	0.1225***	0.0121	0.0031	-4.4361	0.0002**	-0.0022	0.0077	0.5982
			(18.07)		(-5.47)	(-0.75)	(3.02)	(2.91)	(1.38)	(0.33)	(-0.58)	(2.25)	(-0.89)	(1.32)	
				-1.7041***	0.0183***	-0.0008	-0.0015***	-0.1743***	0.0019	0.0123	-3.9570	0.00002	0.0026	0.0019	0.6137
				(-21.55)	(7.20)	(-0.77)	(-3.00)	(-3.92)	(0.24)	(1.18)	(-0.54)	(0.27)	(0.92)	(0.32)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions (cont.)

Panel B: Europe

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1645***					-0.0012	0.00002	0.0001	0.0923***	0.0172***						0.2045
(5.15)					(-0.83)	(0.06)	(0.38)	(4.87)	(4.86)						
	0.2280***				-0.0017	-0.0001	0.0005*	0.0892***	0.0171***						0.2167
	(5.99)				(-1.12)	(-0.16)	(1.67)	(4.84)	(5.12)						
		0.2281***			-0.0014	-0.0001	0.0005*	0.0896***	0.0172***						0.2160
		(6.13)			(-0.99)	(-0.17)	(1.67)	(4.86)	(5.14)						
			1.2497***		-0.0109***	-0.0009***	0.0035***	0.0713***	0.0173***						0.2786
			(26.96)		(-6.38)	(-2.57)	(13.02)	(3.79)	(4.80)						
				-1.0777***	0.0083***	0.0007*	-0.0042***	0.1421***	0.0170***						0.2475
				(-27.58)	(5.82)	(1.80)	(-13.18)	(6.61)	(4.20)						
0.1167***					-0.0011	-0.0008	-0.0004	0.0506*	0.0145***	0.0121***	0.0174	0.0001**	0.0003	-0.0001	0.2295
(3.05)					(-0.57)	(-1.41)	(-1.00)	(1.86)	(3.91)	(2.92)	(0.03)	(2.20)	(0.40)	(-0.07)	
	0.1691***				-0.0020	-0.0008	-0.0001	0.0596**	0.0146***	0.0102**	0.1290	0.0001**	-0.0006	0.0008	0.2380
	(3.82)				(-1.11)	(-1.42)	(-0.24)	(2.23)	(4.18)	(2.28)	(0.27)	(2.29)	(-0.63)	(0.37)	
		0.1701***			-0.0026*	-0.0008	-0.0001	0.0589**	0.0146***	0.0104**	0.1113	0.0001**	-0.0005	0.0007	0.2375
		(4.05)			(-1.65)	(-1.43)	(-0.19)	(2.21)	(4.20)	(2.38)	(0.24)	(2.24)	(-0.54)	(0.35)	
			1.3345***		-0.0158***	-0.0015***	0.0034***	0.0645**	0.0151***	0.0052	0.2658	0.0001**	0.00003	0.0002	0.3026
			(23.82)		(-8.00)	(-2.62)	(9.87)	(2.14)	(4.15)	(1.22)	(0.51)	(2.13)	(0.03)	(0.09)	
				-1.2698***	0.0128***	-0.0003	-0.0045***	0.0630***	0.0134***	0.0203***	0.0058	0.0001**	0.0006	-0.0000	0.2803
				(-23.70)	(6.81)	(-0.69)	(-12.05)	(2.71)	(3.19)	(5.16)	(0.01)	(2.36)	(0.55)	(-0.02)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions (cont.)

Panel C: Asia-Pacific

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1860***					-0.0018	0.0002	-0.0007	0.0843**	0.0070						0.2697
(6.78)					(-1.17)	(0.26)	(-1.61)	(2.01)	(1.21)						
	0.2524***				-0.0024	-0.00002	-0.0004	0.1038***	0.0063						0.2784
	(7.90)				(-1.57)	(-0.04)	(-0.87)	(2.71)	(1.12)						
		0.2515***			-0.0016	-0.00001	-0.0004	0.1038***	0.0065						0.2785
		(7.91)			(-1.02)	(-0.02)	(-0.86)	(2.71)	(1.15)						
			1.0142***		-0.0074***	-0.0011*	0.0014***	0.1498***	0.0056						0.3154
			(20.00)		(-4.46)	(-1.65)	(2.98)	(3.72)	(1.11)						
				-0.7519***	0.0062***	0.0015**	-0.0037***	0.0179	0.0129**						0.2864
				(-17.21)	(3.89)	(2.24)	(-8.35)	(0.43)	(2.01)						
0.1758***					-0.0046**	-0.0002	-0.0001	0.0206	0.0037	0.0042	3.1144	0.0001	0.0014	-0.0004	0.3298
(4.25)					(-2.04)	(-0.23)	(-0.32)	(0.24)	(0.61)	(0.50)	(0.32)	(1.10)	(0.72)	(-0.06)	
	0.1923***				-0.0043*	-0.0004	-0.0001	0.0375	0.0034	0.0011	4.5201	0.0001	0.0018	-0.0010	0.3334
	(4.79)				(-1.74)	(-0.47)	(-0.12)	(0.48)	(0.55)	(0.13)	(0.43)	(1.36)	(0.95)	(-0.18)	
		0.1849***			-0.0040*	-0.0004	-0.0001	0.0415	0.0033	0.0012	4.5583	0.0001	0.0017	-0.0006	0.3334
		(4.75)			(-1.90)	(-0.42)	(-0.18)	(0.55)	(0.53)	(0.14)	(0.44)	(1.37)	(0.88)	(-0.11)	
			1.0606***		-0.0128***	-0.0022**	0.0025***	0.1002	0.0078	-0.0036	1.5520	0.00003	-0.0014	0.0015	0.3732
			(16.11)		(-7.04)	(-2.43)	(4.10)	(1.21)	(1.46)	(-0.41)	(0.18)	(0.36)	(-0.85)	(0.35)	
				-0.9310***	0.0056**	0.0015*	-0.0028***	0.0448	0.0055	0.0193**	-0.2755	-0.00001	0.0043***	0.0025	0.3562
				(-10.07)	(2.11)	(1.65)	(-5.30)	(0.63)	(1.02)	(2.33)	(-0.04)	(-0.18)	(2.56)	(0.43)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions (cont.)

Panel D: South America

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.3115***					-0.0022	-0.0015	0.0003	0.1260**	0.0156***						0.3694
(4.93)					(-0.86)	(-1.31)	(0.37)	(2.12)	(3.00)						
	0.4135***				-0.0036	-0.0012	0.0006	0.1297**	0.0181***						0.3832
	(6.01)				(-1.40)	(-1.07)	(0.76)	(2.17)	(3.40)						
		0.4004***			-0.00006	-0.0012	0.0007	0.1292**	0.0185***						0.3817
		(5.96)			(-0.003)	(-1.09)	(0.80)	(2.16)	(3.47)						
			1.4353***		-0.0134***	-0.0021**	0.0033***	0.1275**	0.0184***						0.4270
			(16.44)		(-5.17)	(-2.16)	(3.45)	(2.15)	(3.45)						
				-0.9536***	0.0121***	-0.0017	-0.0039***	0.1141*	0.0109*						0.3842
				(-10.20)	(4.40)	(-1.37)	(-6.90)	(1.91)	(1.82)						
0.1145***					0.0028	-0.0013	-0.0022**	0.0247	0.0084	0.0358*	-0.2774	0.0002	0.0075	0.0054	0.5481
(1.41)					(0.67)	(-0.78)	(-1.91)	(0.56)	(1.17)	(1.82)	(-0.55)	(1.28)	(1.54)	(0.43)	
	0.1962**				0.0015	-0.0008	-0.0022*	0.0249	0.0079	0.0315*	-0.2936	0.0003	0.0089*	-0.0003	0.5547
	(2.05)				(0.34)	(-0.49)	(-1.93)	(0.57)	(1.19)	(1.67)	(-0.57)	(1.53)	(1.72)	(-0.03)	
		0.1866***			0.0044	-0.0008	-0.0021*	0.0219	0.0084	0.0302*	-0.2400	0.0003	0.0084	0.0009	0.5539
		(2.14)			(1.13)	(-0.50)	(-1.82)	(0.49)	(1.27)	(1.66)	-(0.50)	(1.52)	(1.61)	(0.07)	
			1.4262***		-0.0116**	-0.0032*	0.0007	0.0087	0.0111*	0.0009	0.2031	0.0001	0.0066	-0.0074	0.5806
			(11.13)		(-2.40)	(-1.67)	(0.61)	(0.17)	(1.68)	(0.08)	(0.41)	(0.60)	(1.19)	(-0.48)	
				-1.1872***	0.0198***	-0.0015	-0.0035***	0.1997	0.0110	0.0516**	0.9097	0.0001	0.00001	0.0154	0.5769
				(-7.07)	(5.51)	(-0.82)	(-2.94)	(1.56)	(1.24)	(2.51)	(0.85)	(0.77)	(0.002)	(1.09)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions (cont.)

Panel E: MENA

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.1112**					-0.0001	0.0007	-0.0005	0.1516***	0.0221***						0.3189
(2.31)					(-0.05)	(0.80)	(-0.57)	(3.31)	(3.22)						
	0.2036***				-0.0007	0.0009	-0.0001	0.1728***	0.0222***						0.3308
	(3.86)				(-0.25)	(0.99)	(-0.12)	(3.59)	(3.26)						
		0.1991***			-0.0003	0.0009	-0.0001	0.1744***	0.0224***						0.3307
		(3.72)			(-0.09)	(1.02)	(-0.07)	(3.63)	(3.24)						
			1.2130***		-0.0080***	0.0004	0.0013	0.1739***	0.0263***						0.3759
			(17.15)		(-2.93)	(0.46)	(1.55)	(3.45)	(3.97)						
				-1.0464***	0.0054**	0.0010	-0.0033***	0.0977**	0.0176**						0.3537
				(-12.07)	(2.04)	(1.03)	(-4.30)	(2.44)	(2.35)						
0.0999					0.0015	-0.0031	-0.0006	0.0516	0.0261*	-0.0057	0.2703	0.0001	-0.0012	-0.0004	0.4593
(1.23)					(0.40)	(-1.11)	(-0.86)	(1.08)	(1.78)	(-0.40)	(0.48)	(1.00)	(-0.22)	(-0.05)	
	0.2059**				-0.0072	-0.0001	0.0002	0.0680	0.0413***	-0.0041	0.2535	0.0001	-0.0004	-0.0041	0.4688
	(2.15)				(-0.90)	(-0.03)	(0.28)	(1.38)	(3.41)	(-0.29)	(0.44)	(0.48)	(-0.07)	(-0.56)	
		0.2088**			-0.0075	-0.00003	0.0003	0.0701	0.0416***	-0.0038	0.2989	0.0001	-0.0004	-0.0040	0.4674
		(2.21)			(-1.00)	(-0.01)	(0.41)	(1.43)	(3.42)	(-0.28)	(0.51)	(0.47)	(-0.06)	(-0.54)	
			1.4599***		-0.0072**	-0.0044	0.0015*	0.1021***	0.0251*	-0.0233**	-0.0247	0.0002	0.0007	-0.0046	0.5066
			(12.82)		(-2.04)	(-1.55)	(1.88)	(2.63)	(1.94)	(-1.97)	(-0.04)	(1.71)	(0.12)	(-0.67)	
				-1.1545***	0.0096*	-0.0013	-0.0029***	-0.0039	0.0212	0.0076	0.3432	0.0001	-0.0022	-0.0047	0.4844
				(-9.43)	(1.88)	(-0.45)	(-4.33)	(-0.07)	(1.37)	(0.49)	(0.60)	(0.55)	(-0.43)	(-0.55)	

Table 2.6. Alternative Cross-Sectional Regressions for Regions (cont.)

Panel F: Japan

Range	*SD*	*IVOL*	*MAX*	*MIN*	*BETA*	*ISKEW*	*MV*	*DY*	*StMom*	*EBITDA /EV*	*ES*	*ROE*	*INV*	*NSI*	R^2
0.2012***					-0.0024	-0.0088***	-0.0008	0.3359**	0.0023						0.5581
(3.22)					(-0.90)	(-4.22)	(-1.18)	(2.19)	(0.25)						
	0.3524***				-0.0042	-0.0089***	0.0002	0.3009**	0.0032						0.5636
	(4.73)				(-1.42)	(-4.35)	(0.36)	(2.03)	(0.36)						
		0.2904***			0.0002	-0.0088***	0.0002	0.2935*	0.0039						0.5624
		(4.54)			(0.07)	(-4.28)	(0.33)	(1.95)	(0.44)						
			1.0233***		-0.0112***	-0.0119***	0.0003	0.3905***	0.0027						0.5738
			(12.73)		(-3.86)	(-5.60)	(0.54)	(2.68)	(0.32)						
				-1.2440***	0.0130***	-0.0022	-0.0035***	0.1170	0.0045						0.5730
				(-10.70)	(4.75)	(-0.89)	(-4.72)	(0.72)	(0.51)						
-0.0101					0.0013	-0.0105**	-0.0021**	0.1983	-0.0098	-0.0273	0.6218*	0.00004	-0.0024	-0.0357	0.8138
(-0.11)					(0.32)	(-2.27)	(-2.22)	(0.49)	(-0.63)	(-0.80)	(1.82)	(0.10)	(-0.16)	(-0.91)	
	0.1349				-0.0030	-0.0107**	-0.0009	0.2259	-0.0102	-0.0381	0.5295*	0.0001	0.0004	-0.0358	0.8122
	(1.08)				(-0.53)	(-2.23)	(-0.84)	(0.57)	(-0.64)	(-1.08)	(1.69)	(0.36)	(0.03)	(-0.89)	
		0.1133			-0.0006	-0.0111**	-0.0007	0.2733	-0.0082	-0.0413	0.5899*	0.0002	0.0014	-0.0332	0.8125
		(1.18)			(-0.15)	(-2.33)	(-0.63)	(0.67)	(-0.51)	(-1.15)	(1.85)	(0.46)	(0.09)	(-0.82)	
			0.9025***		-0.0106**	-0.0106**	0.0008	-0.0606	-0.0067	-0.0378	0.2705	0.0001	-0.0078	-0.0250	0.8189
			(6.69)		(-2.48)	(-2.25)	(0.91)	(-0.18)	(-0.49)	(-1.03)	(0.99)	(0.21)	(-0.62)	(-0.70)	
				-1.5063***	0.0128***	-0.0056	-0.0045***	0.2801	0.0078	-0.0039	0.6695*	-0.0001	0.0190	-0.0135	0.8261
				(-8.16)	(2.71)	(-1.30)	(-3.94)	(0.60)	(0.46)	(-0.12)	(1.86)	(-0.41)	(1.29)	(-0.33)	

CHAPTER 3

DECOMPOSING THE EARNINGS-TO-PRICE RATIO AND THE CROSS-SECTION OF INTERNATIONAL EQUITY-INDEX RETURNS

3.1. Introduction

In finance literature, the relation between the expected stock returns and the value effect related with earnings is widely reported. The value effect is first documented by Basu (1977, 1983) based on price-to-earnings (*PE*) ratio and it is concluded that portfolios with low *PE* ratio stocks generate higher average risk-adjusted returns than portfolios with high *PE* ratio stocks. Earlier studies have also examined the value effect at the international index level. According to these studies, indexes with high earnings-to-price (*EP*) ratios generate relatively high returns compared to the indexes with low *EP* ratios (Macedo, 1995; Kim, 2012; Angelidis & Tessaromatis, 2014; Zaremba, 2016b; Umutlu & Bengitöz, 2020).

In this dissertation chapter, the studies about the value effect performed at firm level are extended to an international level by considering both country-industry indexes and country indexes. Moreover, in the sense of Fama and French (2008), who decompose the book-to-market (*BM*) ratio at the stock level, it is the first study that decompose the earnings-to-price (*EP*) ratio at index level into four components namely, momentum, reversal, change in earnings, and lagged *EP*. I investigate whether these components contain independent information beyond *EP* alone that can improve the estimation of expected returns on country-industry and country indexes. In addition, the decomposition analyses are also performed for different sub-samples as developed and emerging markets; different size portfolios; different regions and for different time horizons of lagged value of *EP*.

Some of the components obtained from the decomposition corresponds to well-known factors that are documented in the asset-pricing literature. For instance, the momentum effect (Jegadeesh & Titman, 1993) and the reversal effect (DeBondt & Thaler, 1985) have been detected as determinants of asset returns for a long time. In general, momentum (*MOM*) is the cumulative return in months from *t*-12 to *t*-1; the long-run reversal (*REV*) is the cumulative return in months from *t*-60 to *t*-12. Moreover, the change in earnings (*dE*), which is introduced by Fama and French (2015), is defined as the change in earnings from month *t*-60 to *t*-1. The last component is the 60-month lagged value of earnings-to-price ratio (*LEP*). In addition to the decomposition analyses with 60-months lagged value of *EP*, I also use 36-months and 48-months lagged values of *EP* to examine the results for different time horizons. The sample includes monthly data for 51 countries from January 1973 to July 2017. Moreover, I use 19 different *supersectors* specified for 51 countries to track country-industry indexes. In addition, the country indexes are used as an alternative sample of international indexes.

The results show that there is a consistently significant earnings-to-price ratio effect for the full and developed samples of country-industry indexes and for the full, developed, and emerging samples of country indexes. Moreover, the significance of the *EP* ratio does not hold for all three lags of *EP* in emerging samples of country indexes. The significance of the *EP* ratio effect changes depending on the regions of country-industry indexes and the size portfolios of both country-industry and country indexes. In addition, it is concluded that decomposing the *EP* ratio does matter depending on the samples; sub-samples; and lags of *EP*. More specifically, the components of *EP* reveal independent information beyond the *EP* ratio alone that provides more accurate estimates of future returns for the full and developed samples of country-industry indexes; and for the full, developed, and emerging samples of country indexes. On the other hand, for the emerging sample of country-industry indexes decomposition of *EP* is valid only when 36-months and 60-months lagged values of *EP* are used. Additionally, regional analyses show that the components of *EP* bring into open information in *EP* and cause enhancement in the estimates of expected returns for North America, Europe, Asia, the Middle East and South Africa (MENA), and Japan. However, in South America there is not enough evidence to conclude that the decomposition of *EP* does matter when 36-months and 60-months lagged values of *EP* are used. Furthermore, size portfolio analyses also show that components of *EP* reveal more information in the portfolios including country-industry and country indexes with low market capitalization values.

This dissertation chapter contributes to the finance literature in several ways. Firstly, the value effect (based on book-to-market ratio, price-to-earnings ratio or earnings-to-price ratio) is dominantly examined at the stock level (Basu, 1977, 1983; La Porta, 1996) and country level (Macedo, 1995, Kim, 2012; Angelidis & Tessaromatis, 2017). These studies are extended to an international level by performing analyses at the country-industry level as well. Moreover, the value effect is explored based on earnings-to-price ratio, which is documented to be a strong determinant of international index returns. Secondly, as far as I know, the *EP* ratio is first decomposed into its components in this dissertation chapter. A decomposition analysis at the index level is first conducted by Zaremba and Umutlu (2018) for the size effect. This study is similar to that of Zaremba and Umutlu (2018) in the sense that both studies conduct decomposition analyses at the index level. On the other side, this dissertation chapter differs from Zaremba and Umutlu (2018) in decomposing the *EP* effect. In addition, the effectiveness of decomposition of *EP* is explored over different time horizons by examining the significance of *EP* at different lags. In other words, I examine whether recent news is more relevant than older news in predicting future returns, as Fama and French (2008) discuss. Furthermore, the decomposition analyses are also performed for developed and emerging markets of country-industry and country indexes; regional samples of industry indexes; and size portfolios of country-industry and country indexes.

The third dissertation chapter is organized as follows. Section 3.2 describes the data and its sources. Section 3.3 provides a brief literature review about the value effect. Section 3.4 summarizes some studies (fundamentally Fama & French, 2008) that performs decomposition analyses. Section 3.5 explains the steps of decomposition of *EP*. Section 3.6 shows the significance tests of the decomposition of *EP*. Section 3.7 presents the results for industry and country indexes, regions, and size portfolios. Lastly, Section 3.8 concludes the dissertation chapter.

3.2. Data and Variables

This dissertation chapter also uses the same dataset for country-industry indexes that is used in the previous chapter. In addition to country-industry indexes sample, this dissertation chapter also uses local stock market indexes as an alternative international sample. In summary, the dataset, which is obtained from Datastream, includes monthly time-series price-to-earnings ratio, US-dollar dominated return index and price index for country-industry and country indexes from January 1973 to July 2017. Moreover, monthly risk-free rate is obtained by using the one-month Treasury bill rate from Kenneth. R. French's data library[11].

For the sample of country-industry indexes, local *supersector* based on the Industry Classification Benchmark (ICB) of FTSE[12] are used. Moreover, for the sample of local stock market indexes Datastream market indexes are used. A total of 51 stock markets, of which 23 are developed and 28 are emerging, are analyzed. Country-industry and country indexes in each sample are employed as individual international assets, which are used by international investors in trading strategies.

Table 3.1 and 3.2 show the overview of the local industry and country indexes, respectively. In Table 3.1, firstly, the cross-sectional averages of monthly values of each supersector indexes are calculated across 51 markets for each month. Then, the time-series statistics for each index are calculated. On the other hand, in Table 3.2, basic statistics are calculated by using monthly values of each country indexes.

< Table 3.1 >

< Table 3.2 >

3.3. The Value Effect

The value effect states that low priced stocks according to their earnings, dividends, debt, or book value of equity generate higher long-run returns than high priced stocks according

[11] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[12] The supersector definitions and the ICB structure are comprehensively documented in the following link: www.icbenchmark.com.

to these measures of value[13]. One of the important study for the measures of value is documented by Basu (1977, 1983), who focused on price-to-earnings (*PE*) ratio, concluded that portfolios including stocks with low *PE* ratio generate higher average risk-adjusted returns than portfolios including stocks with high *PE* ratio. Moreover, earlier studies also examined the relationship between measures of value and expected returns across country indexes (Macedo, 1995). Country-level study of Angelidis and Tessaromatis (2014) stated that stocks that have low price-to-earnings ratio outperform the stocks that have high price-to-earnings ratio. In addition, the results for price-to-earnings ratio from the study of Zaremba (2016b), who also conducted country-level study about the relationship between fifty different stock related variables and expected returns, are consistent with the study of Angelidis and Tessaromatis (2014).

In this dissertation chapter, I focus on earnings-to-price ratio (*EP*), which is the reverse of the price-to-earnings ratio. *EP* is defined as the division of the earnings per share by the share price. Beyond the studies that examined price-to-earnings ratio at the stock and index level, the *EP* ratio is decomposed into four separate components and investigate the impact of these components on the predictive power of the earnings-to-price effect.

3.4. Decomposition Analyses

Decomposition analyses are first conducted by Fama and French (2008) to explore the contribution of the components of book-to-market (*BM*) ratio in predicting expected returns. They indicate that since *BM* ratio varies with expected cash flows, it is a noisy measure of expected stock returns for US equity market. They hypothesize that decomposing *BM* ratio in terms of past changes in book equity and price can generate independent information about expected cash flows. Therefore, this independent information can be used to improve estimates of expected returns. Fama and French decompose logarithm (log) of *BM* ratio at time *t* into three components, which are log of

[13] Earnings: Basu (1977) and Jaffe, Keim, & Westerfield (1989). Dividends: Lakonishok, Shleifer, & Vishny (1994). Debt: Bhandari (1988). Book value of equity: Rosenberg, Reid, & Lanstein (1985), Fama & French (1992, 1993), and Chan, Jegadeesh, & Lakonishok (1995). Cash flow: Chan & Lakonishok (2004).

BM ratio at *t-k*, change in log of book equity from *t-k* to *t*, and change in log of price from *t-k* to *t* as shown in Equation (3.1).

$$BM_t = BM_{t-k} + dB_{t-k} - dM_{t-k} \tag{3.1}$$

They investigate their decomposition approach empirically for microcap stocks and all but microcap stocks trading in US equity market from July 1927 to December 2006. All but microcap stocks are defined as the NYSE, AMEX, and NASDAQ stocks that are above the twentieth percentile of market capitalization for NYSE stocks. On the other hand, microcap stocks are those that are below the twentieth percentile of market capitalization for NYSE stocks. According to the firm level cross-sectional regression results, they conclude that three components of *BM* ratio contribute to the predictive power of *BM* ratio in estimating expected returns. In other words, these components provide more accurate estimates of expected returns than *BM* alone. Additionally, it is indicated that recent changes in book equity and price are more relevant than more distant changes in predicting returns.

Bali, Cakici, and Fabozzi (2013) use the decomposition approach of Fama and French for the *BM* ratio effect and investigate for six non-US G7 countries, which are the United Kingdom, Germany, France, Italy, Canada, and Japan. The data includes common stocks listed on each country's major stock exchange(s) from December 1979 to June 2007. It is concluded that decomposing *BM* ratio into its components also enhances estimates of expected returns for the stocks traded in non-US G7 countries' stock markets. In other words, decomposition generates more information about the expected cash flows. Moreover, like Fama and French (2008), they also indicate that recent changes in book equity and price have more relevant information than older changes in those about expected cash flows and expected returns. In addition, it is pointed out that their results are robust to long-term predictability and under the control of momentum.

Cakici, Chatterjee, and Topyan (2015) test the significance of the *BM* ratio decomposition approach of Fama and French (2008) for Chinese shares trading in Shanghai and Shenzhen stock markets between January 1996 and December 2012. Consistent with the results of Fama and French (2008), they find that change in book equity is not much important for small stocks, however, unlike Fama and French (2008), they indicate that change in price have a significant role in explaining expected returns for small stocks. Moreover, in contrast to Fama and French (2008), they state that the contribution of change in book equity is much more than the contribution of change in price for large stocks. On the other hand, net share issue and momentum do not contribute to the explanatory power of the regression. As a result, they point out that *BM* ratio decomposition improves the explanatory power of the cross-sectional regression than *BM* ratio alone.

Blackburn and Cakici (2019) also decompose the *BM* ratio for the global stocks traded in 23 global markets, which are grouped as four distinct global regions of North America, Europe, Japan, and Asia, from 1991 to 2016. They use the same set of countries with the study of Fama and French (2012) having one difference that replacing Greece with Israel. They conclude that changes in book value is an important component of *BM* ratio, since it consistently affects expected returns for all types of markets and different sub-periods. For all global regions with the exception of Japan, it is pointed out that net share issue also generates accurate explanatory power on expected returns. Moreover, the results of decomposition analyses for different time horizons indicate that the information from 12 months prior values of change in book value, price, and net share issuance are more relevant than the ones from 36 months prior values of these components. As a result, they find enough evidence to conclude that breaking *BM* ratio into its components enhances the estimates of expected returns across global markets.

Different from the previous decomposition studies, Zaremba and Umutlu (2018) decompose market value and they extend the literature to an international level by using country and industry indexes. Dataset includes monthly time-series data from January 1973 to January 2017 for 51 countries, including developed, emerging and frontier markets. Moreover, for industry indexes they used 19 supersector indexes for 51 countries. They decompose market value into four different variables, which are momentum, reversal, impact of issuance, and lagged value of market value. The analyses results indicate that there is a significant size effect across both countries and industries. Decomposition of market value showed that for country and industry indexes size premia has two sources, which are lagged market value and long-run reversal. They also find that there is a significant issuance effect in industry returns and a significant relation between index returns (both country and industry indexes) and January effect.

3.5. Decomposition of the Earnings-to-Price (*EP*) Ratio

In this dissertation chapter, for both country and industry indexes the *EP* ratio is decomposed into four independent components, whose effects on asset returns are dominantly investigated at the stock and index level. These components are long-run *EP* ratio, momentum, reversal, and change in earnings.

The momentum effect (*MOM*), proposed by Jegadeesh and Titman (1993), states that stocks that have performed well in the previous months from *t*-12 to *t*-6 are tend to outperform in the future. Another important study about momentum effect is conducted by Levy (1967) and concludes that there is a positive relationship between the previous 27-week moving-average stock price and future stock returns. Moreover, beyond stock-level analyses, momentum effect is also examined in international equity markets (Bhojraj & Swaminathan, 2006; Bali, Cakici, & Whitelaw, 2011; Fama & French, 2012; Asness, Moskowitz, & Pedersen, 2013; Zaremba, 2016a; Zaremba, Umutlu, & Karathanasopoulos, 2019, Umutlu & Bengitöz, 2020). In the decomposition of *EP*, momentum is defined as the change in return from month *t*-12 to *t*. *MOM* is calculated by dividing Return Index in month *t* to Return Index in month *t*-12 $\left({RI_t}/{RI_{t-12}}\right)$.

The long-run reversal effect (REV_k) is fundamentally documented by DeBondt and Thaler (1985). Reversal effect states poorly performing stocks and well-performing stocks in the previous 3 to 5 years are tend to experience reversal performance in the following period. Moreover, Richards (1997), Balvers and Wu (2006), and Malin and Bornholt (2013) examine reversal effect for country indexes. In this dissertation chapter, reversal is defined as the change in return from month *t-k* to *t*-12. *k* shows the lag lengths of 36-, 48-, and 60-months. REV_k is calculated by dividing Return Index in month *t*-12 to Return Index in month *t-k* $\left({RI_{t-12}}/{RI_{t-k}}\right)$.

The change in earnings (dE_k), which is known as the measure of the profitability effect introduced by Fama and French (2015), is defined as the change in earnings from month *t-k* to *t*. Similar with REV_k, *k* represents the lag lengths of 36-, 48-, and 60-months. However, Datastream does not include earnings data for country-industry and country indexes. Therefore, Price-to-Earnings (*PE*) ratio and Price Index (*PI*) data from

Datastream are used to obtain change in earnings value by making some derivations. Firstly, *PE* values in month *t* and in month *t-k* are defined as X_t and X_{t-k}, respectively, as shown in Equation (3.2).

$$\frac{PE_t}{PE_{t-k}} = \frac{X_t}{X_{t-k}} \tag{3.2}$$

Later, in Equation (3.3), *PE* value in month *t* is divided by *PE* value in month *t-k* and some arrangements are made to obtain change in earnings value.

$$\frac{X_t}{X_{t-k}} = \frac{P_t}{E_t} x \frac{E_{t-k}}{P_{t-k}} = \frac{P_t}{P_{t-k}} x \frac{E_{t-k}}{E_t} \tag{3.3}$$

If earnings proportion is left alone in the left side of the equation, change in earnings value can be obtained as in Equation (3.4).

$$\frac{E_t}{E_{t-k}} = \frac{P_t}{P_{t-k}} x \frac{X_{t-k}}{X_t} \tag{3.4}$$

Since X_{t-k} and X_t values are defined as the *PE* values in month *t-k* and *t*, respectively, *X* values can be written in terms of *PE* values. Moreover, since Datastream does not provide Price data for country-industry and country indexes, Price Index (*PI*) data is used instead, which provides almost the same proportional values with Price data. As a result, change in earnings (dE_k) in time *t* is defined as in Equation (3.5).

$$dE_k = \frac{E_t}{E_{t-k}} = \frac{PI_t}{PI_{t-k}} x \frac{PE_{t-k}}{PE_t} = \frac{{PI_t}/{PI_{t-k}}}{{PE_t}/{PE_{t-k}}} \tag{3.5}$$

The lagged earnings-to-price ratio (LEP_k) is generated after defining three components (MOM, REV_k, dE_k) and it shows the long-run *EP* value. LEP_k is defined as the earnings-to-price ratio in month *t-k* (EP_{t-k}). In this dissertation chapter, *k* is defined as 36-, 48-, and 60-months lagged values of *EP*.

Decomposition of *EP* ratio aims to investigate whether the components of the *EP* ratio have additional information that enhance the estimates of expected returns. Starting from this point of view, decomposition of *EP* firstly starts with splitting *EP* at time *t* into *k*-months lagged value of *EP*, which is defined as EP_{t-k} (LEP_k) and subsequently extracting change in earnings from months *t-k* to *t*. Therefore, Equation (3.6) is obtained

$$EP_t = \frac{E_t}{P_t} = \frac{E_{t-k}}{P_{t-k}} x \frac{E_t}{E_{t-k}} x \frac{P_{t-k}}{P_t} \tag{3.6}$$

In Equation (3.6), the last term, ${P_{t-k}}/{P_t}$, is the remaining variable after decomposing *EP* into LEP_k and dE_k. Thereafter, that variable is separated into reverse of the momentum, which shows price change from months *t*-12 to *t*, and reverse of the reversal, which shows price change from months *t*-*k* to *t*-12.

$$EP_t = \frac{E_t}{P_t} = \frac{E_{t-k}}{P_{t-k}} x \frac{E_t}{E_{t-k}} x \frac{P_{t-12}}{P_t} x \frac{P_{t-k}}{P_{t-12}} \tag{3.7}$$

Finally, to represent *EP* ratio in terms of the summation of four independent components, I take the logarithm of both sides.

$$\ln(EP_t) = \ln(EP_{t-k}) + \ln\left(\frac{E_t}{E_{t-k}}\right) + \ln\left(\frac{P_{t-12}}{P_t}\right) + \ln\left(\frac{P_{t-k}}{P_{t-12}}\right) \tag{3.8}$$

In Equation (3.8), I take the reverse of the last two components to obtain logarithm of *MOM* and *REV*.

$$\ln(EP_t) = \ln(EP_{t-k}) + \ln\left(\frac{E_t}{E_{t-k}}\right) - \ln\left(\frac{P_t}{P_{t-12}}\right) - \ln\left(\frac{P_{t-12}}{P_{t-k}}\right) \tag{3.9}$$

By defining the variables in Equation (3.9) as earnings-to-price ratio (*EP*), lagged earnings-to-price ratio (*LEP*), change in earnings (*dE*), momentum (*MOM*), and reversal (*REV*), I can write Equation (3.9) simply as:

$$EP = LEP + dE - MOM - REV \tag{3.10}$$

The effectiveness of *EP* decomposition is explored over different time horizons by using *k*-months lagged values of *EP*. Therefore, the importance of recent news over older news in predicting returns can be examined for different time horizons. In this dissertation chapter, I use 36-months, 48-months, and 60-months lagged values of *EP*, which are represented as $EP_{t\text{-}36}$ (LEP_{36}), $EP_{t\text{-}48}$ (LEP_{48}), and $EP_{t\text{-}60}$ (LEP_{60}), respectively.

The decomposition equations for the three different lag lengths of 36-, 48-, and 60-months are shown in Equations (3.11), (3.12), and (3.13), respectively.

$$\ln(EP_t) = \ln(EP_{t-36}) + \ln\left(\frac{E_t}{E_{t-36}}\right) - \ln\left(\frac{P_t}{P_{t-12}}\right) - \ln\left(\frac{P_{t-12}}{P_{t-36}}\right) \tag{3.11}$$

$$\ln(EP_t) = \ln(EP_{t-48}) + \ln\left(\frac{E_t}{E_{t-48}}\right) - \ln\left(\frac{P_t}{P_{t-12}}\right) - \ln\left(\frac{P_{t-12}}{P_{t-48}}\right) \tag{3.12}$$

$$\ln(EP_t) = \ln(EP_{t-60}) + \ln\left(\frac{E_t}{E_{t-60}}\right) - \ln\left(\frac{P_t}{P_{t-12}}\right) - \ln\left(\frac{P_{t-12}}{P_{t-60}}\right) \tag{3.13}$$

3.6. Does Decomposition of *EP* Matter?

In this section, I examine whether decomposing *EP* in terms of lagged value of *EP*, change in earnings, momentum and reversal can be used to enhance estimates of expected returns. In other words, following the decomposition approach of Fama and French (2008), it is tested that whether the components of *EP* ratio reveal additional information that can be used to explain future returns better than *EP* ratio alone. If the components do not include independent information, then decomposition of *EP* will be failure. It means that none of the components of *EP* ratio contributes to the predictive power of the model.

Decomposition analyses are first introduced by Fama and French (2008) to investigate the ability of the components of book-to-market ratio in explaining expected returns. They perform Fama and MacBeth (1973) regression approach to obtain average slope estimates from monthly cross-sectional regressions of stock returns on book-to-market equity and four decomposition variables. Equation (3.14) shows the basic Fama-MacBeth regression including *EP* ratio as the only independent variable.

$$R_{i,t+1} = \beta_{0,t} + \beta_{1,t}EP_{i,t} + \varepsilon_{i,t+1} \tag{3.14}$$

EP components can be written instead of *EP* in Equation (3.14) to obtain Equation (3.15).

$$R_{i,t+1} = \alpha_{0,t} + \alpha_{1,t}LEP_{i,t} + \alpha_{2,t}dE_{i,t} + \alpha_{3,t}MOM_{i,t} + \alpha_{4,t}REV_{i,t} + \varepsilon_{i,t+1} \tag{3.15}$$

For Equation (3.15), in the sense of Fama and French (2008) methodology, the null hypothesis says that breaking *EP* ratio into its components does not improve the estimates of expected returns than *EP* alone. According to null hypothesis, true slopes for *LEP*, *dE*, *MOM*, and *REV* should have the same value in magnitude. Moreover, the true slopes for *LEP* and *dE* should be positive; for *MOM* and *REV* should be negative. Therefore, if all the coefficients are the same then the decomposition variables in Equation (3.15) can be written as coefficient parenthesis, so *EP* value is obtained. In other words, Equation (3.15) reduces to Equation (3.14) and *EP* becomes the only variable in predicting expected returns. As a result, it can be concluded that *EP* components do not statistically increase the predictability of expected returns and it does not matter whether decomposing *EP*. On the other hand, if not all coefficients for the decomposition variables are equal to each other, it can be concluded that components of *EP* include different mixes of information about expected returns.

Fama and French (2008) suggest a simple way to test whether the true slopes for the decomposition variables in Equation (3.15) are equal to the slope for *EP* in magnitude. They propose an alternative regression that uses the most recent *EP* ratio instead of lagged value of *EP* in Equation (3.15).

$$R_{i,t+1} = b_{0,t} + b_{1,t}EP_{i,t} + b_{2,t}dE_{i,t} + b_{3,t}MOM_{i,t} + b_{4,t}REV_{i,t} + \varepsilon_{i,t+1} \tag{3.16}$$

where $R_{i,t+1}$ is the excess returns on the index *i* in month *t*+1; $EP_{i,t}$ is the log of *EP* on the index *i* in month *t*; $LEP_{i,t}$ is the log of *LEP* (*EP* value in month t-*k*) on the index *i* in month *t*; $dE_{i,t}$ is the log of *dE* (change in earnings from month *t*-*k* to *t*) on the index *i* in month *t*; $MOM_{i,t}$ is the log of *MOM* (momentum from month *t*-12 to *t*) on the index *i* in month *t*; $REV_{i,t}$ is the log of *REV* (reversal from month *t*-*k* to *t*-12) on the index *i* in month *t*; *k*=36-, 48-, and 60-months.

Since $EP = LEP + dE - MOM - REV$, I substitute the *EP* components presented in Equation (3.10) for *EP* in Equation (3.16) to test whether $a_{1,t} = a_{2,t}$, $a_{1,t} = -a_{3,t}$, $a_{1,t} = -a_{4,t}$. After some arrangements, the Equation (3.17) is generated:

$$\begin{aligned} R_{i,t+1} = b_{0,t} + b_{1,t}LEP_{i,t} + \left(b_{1,t} + b_{2,t}\right)dE_{i,t} + \left(b_{3,t} - b_{1,t}\right)MOM_{i,t} \\ + \left(b_{4,t} - b_{1,t}\right)REV_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3.17}$$

When the coefficients of the components in Equation (3.15) and those in Equation (3.17) are compared, it is obtained that $a_{1,t} = b_{1,t}$, $a_{2,t} = b_{2,t} + b_{1,t}$, $a_{3,t} = b_{3,t} - b_{1,t}$, $a_{4,t} = b_{4,t} - b_{1,t}$. Starting from the first equality, $a_{1,t} = b_{1,t}$, I substitute $a_{1,t}$ for $b_{1,t}$ in other equalities. Therefore, I have the following equations, which express the coefficients *b* in terms of coefficients *a*: $b_{2,t} = a_{2,t} - a_{1,t}$, $b_{3,t} = a_{3,t} + a_{1,t}$, $b_{4,t} = a_{4,t} + a_{1,t}$.

The equations above show that testing whether $b_{2,t} = 0$, $b_{3,t} = 0$, and $b_{4,t} = 0$ in Equation (3.16) is equivalent to testing whether $a_{2,t} = a_{1,t}$, $-a_{3,t} = a_{1,t}$, $-a_{4,t} = a_{1,t}$.

Therefore, the hypotheses of $a_{2,t} + a_{3,t} = 0$ (*dE*+*MOM*=0), $a_{2,t} + a_{4,t} = 0$ (*dE*+*REV*=0), and $a_{3,t} - a_{4,t} = 0$ (*MOM-REV*=0) are tested by using the coefficient estimates from Equation (3.15).

The first three testable hypotheses ($b_{2,t} = 0$, $b_{3,t} = 0$, and $b_{4,t} = 0$) are tested by performing cross-sectional regression of Equation (3.16) for each month. Thereafter, the time-series means of the coefficients over the months in the sample period and the corresponding Newey-West adjusted t-statistics are calculated. As a result, it is tested that whether the slopes for *dE*, *MOM*, and *REV* are equal to zero. Moreover, the last three testable hypotheses ($a_{2,t} + a_{3,t} = 0$, *dE*+*MOM*=0; $a_{2,t} + a_{4,t} = 0$, *dE*+*REV*=0; $a_{3,t} - a_{4,t} = 0$, *MOM-REV*=0) are tested by using the monthly estimated coefficient values of $a_{2,t}$, $a_{3,t}$, and $a_{4,t}$ from the cross-sectional regression of Equation (3.15). Firstly, *dE*+*MOM*, *dE*+*REV*, and *MOM-REV* summations and difference are calculated for each month in the sample period by using the coefficient estimates from Equation (3.15). Then, time-series averages over the months are calculated for *dE*+*MOM*, *dE*+*REV*, and *MOM-REV*. Moreover, the Newey-West adjusted t-statistics are also calculated. The testable hypotheses are shown in below:

H_1: $b_{2,t} = a_{2,t} - b_{1,t} = a_{2,t} - a_{1,t} = 0$ $\qquad$ H_4: $a_{2,t} + a_{3,t} = 0$

H_2: $b_{3,t} = a_{3,t} + b_{1,t} = a_{3,t} + a_{1,t} = 0$ $\qquad$ H_5: $a_{2,t} + a_{4,t} = 0$

H_3: $b_{4,t} = a_{4,t} + b_{1,t} = a_{4,t} + a_{1,t} = 0$ $\qquad$ H_6: $a_{3,t} - a_{4,t} = 0$

If all the hypotheses cannot be rejected, then the decomposition does not add power to the prediction of future returns. Rejecting any of the hypothesis implies that decomposing *EP* into its components reveals additional significant information that is not included in *EP* ratio alone.

3.7. Results

3.7.1. Country-Industry Indexes

The sample of country-industry indexes includes 19 *supersector* indexes specified for 51 countries traded from January 1973 and July 2017. The analyses steps for decomposition of *EP* and Fama-MacBeth regressions are performed for each month across indexes. Then, time-series averages of the slope coefficients over the months in the research period and the Newey-West adjusted t-statistics are calculated. Table 3.3 summarizes the results of the regression equations (3.14), (3.15), and (3.16) in specifications (1), (2), and (3) for the different lags of *EP*, which are 36-, 48-, and 60-months. In addition to the results of the full sample analyses presented in Panel A, I divide the full sample as developed and emerging markets, whose analyses results are presented in Panels B and C, respectively.

< Table 3.3 >

The results for the full sample indicate that the log of EP_t, which is included in the baseline regression in specification (1) and also in specification (3), is a consistently significant explanatory variable with the t-statistics spreads from 2.93 to 3.70. In addition, in the regression (3.15), which includes 36-, 48-, and 60-months lagged values of *EP*, LEP_k values are also statistically significant with the corresponding t-statistics of 3.33, 3.39, and 3.61, respectively. Moreover, in specification (2), monthly coefficient estimates from the regression equation (3.15) are used to test whether the average values of the sums of dE_k+*MOM*, dE_k+REV_k, and the average values of the difference of *MOM*-REV_k are equal to zero. If so, it can be inferred that change in earnings, momentum, and reversal have almost the same effect on expected returns and therefore, the origins of earnings-to-price ratio are not able to enhance the estimation of expected returns. In the full sample, all of the sums and difference are statistically different from zero with strong t-statistics varying from 2.59 to 4.79 in magnitude, which means that coefficients for the components are different from each other on average. Additionally, results for Equation (3.16) indicate that decomposition variable *MOM* is consistently significant when *k*=36, 48, and 60-months with the strong t-statistics spreading from 2.70 to 3.95. Decomposition equations indicate that testing whether slope for *MOM* $(b_3 = a_3 + a_1)$ is statistically different from zero is equivalent to testing whether the summation of slope coefficients of a_1 and a_3 from Equation (3.15) are statistically different from zero. Based on the statistically significant and positive slope for *MOM*, it can be said that the coefficient for *MOM* is greater than the one for *EP* in magnitude. Moreover, testing whether $b_3 = a_3 + a_1 = 0$ is also equivalent to testing whether $a_2 + a_3 = 0$ and $a_3 + a_4 = 0$ in Equation (3.15). In addition, when *k* is 36-months, *MOM* and REV_k; when *k* is 48-months, only *MOM*; and when *k* is 60-months, all decomposition variables are statistically significant. As a result, it can be concluded that not all of the slope estimates of *EP* components are statistically equal to each other. It means that components include independent information that can enhance the estimates of expected returns. According to these results, it can be suggested that momentum is an important component for the full sample of country-industry indexes in estimating expected returns for all three different lags of *EP*.

The results for the developed country-industry indexes in Panel B of Table 3.3 show that EP_t is statistically significant only in the regression (3.15) of specification (3) having coefficients of 0.0026,0.0027, and 0.0026 with the corresponding t-statistics of 2.32, 2.36, and 2.34, respectively. LEP_k are also significant in specification (2) with the coefficients of 0.0026, 0.0027, and 0.0026 and the corresponding t-statistics of 2.25, 2.28, and 2.25. However, their coefficients and t-statistics are similar to each other and it gives no guarantee about the relation between recent and older news. In specification (2), all of the average values of the sums and difference between the monthly coefficients from regression equation (3.15) are statistically different from zero with the t-statistics spreads from -1.70 to 4.78. In addition, in specification (3), the components of *MOM* for all three different time horizons and REV_k when k is 36-months are statistically significant. These results imply that on average components have different effects on expected returns. Therefore, it can be inferred that using the components of *EP* to predict returns provides more accurate estimates of expected returns than *EP* alone.

For the emerging country-industry indexes, while EP_t ratio is statistically significant in specification (1) and specification (3) when k=60-months, only LEP_{60} is significant in specification (2). Also, the coefficients for EP_t (0.0099 and 0.0088) are greater than the ones for LEP_{60} (0.0055). It implies that recent news is more relevant than prior news for *EP*. Moreover, the monthly coefficients from Equation (3.15) in specification (2) show that the difference between *MOM* and REV_k (when k=36- and 60-months) and the sum of dE_k and *MOM* (when k=60-months) are statistically different from zero with t-statistics of 1.79, 3.08, and 1.74, respectively. This result indicates that *MOM* and REV_k; dE_k and REV_k are significantly different from each other and have different effects on expected returns. In addition, the results of Equation (3.16) indicate that *MOM* $(b_3 = a_3 + a_1)$ is statistically significant only when k=60-months, which means that its slope coefficient is different from *EP* in magnitude. Therefore, it can be concluded that components of *EP* reveal information that is buried in *EP* alone and this information increase the estimates of expected returns only when 36- and 60-months lagged values of *EP* are used. On the other hand, since none of the average values of the difference/summations in Equation (3.15) and none of the components in Equation (3.16) is statistically significant, it can be inferred that decomposition of *EP* is a failure when 48-months lagged value of *EP* is used.

In summary, for the full sample and developed sample of country-industry indexes, EP_t is statistically significant for the three different lags of *EP*. However, for the emerging sample EP_t is only significant in specification (1) and specification (3) (when k=60-months). Moreover, there is no monotonic decrease or increase in the coefficients for LEP_k through k=36-months to k=60-months for the all three samples. Therefore, there is no evidence about the importance of recent news over older news in general. The results indicate that breaking *EP* ratio into three different components unlocks information about returns that increase the estimates of expected returns for the full sample and developed country-industry indexes when all three different lags of *EP* are used. Moreover, for the emerging country-industry indexes *EP* decomposition is significant only when 36- and 60-months lagged values of *EP* are used. However, for the emerging country-industry indexes there is no evidence that decomposition of *EP* does matter when 48-months lagged value of *EP* is used. In addition, *REV* provides significant results for the full and developed samples in some cases whereas *MOM* is consistently significant for the full and developed samples of country-industry indexes for three different lags of *EP* and for the emerging sample when k=60-months. As a result, in general, it can be inferred that momentum effect for all three country-industry index samples and reversal effect for the developed and emerging country-industry samples are important components of *EP* that enhance the estimates of expected returns.

3.7.2. Country Indexes

In this section, the decomposition analyses are performed for local stock market indexes, which include 51 countries traded from January 1973 and July 2017. Table 3.4 presents the average coefficients and the Newey-West (1987) t-statistics of the regression equations (3.14), (3.15), and (3.16) in specifications (1), (2), and (3) for the full sample of country indexes as well as sub-samples of developed and emerging county indexes.

Moreover, the analyses are performed for the different lags of *EP*, which are 36-, 48-, and 60-months.

< Table 3.4 >

For the full sample, the results show that EP_t is strongly statistically significant in the specifications (1) and (3) with the coefficients varying from 0.0053 to 0.0072. Moreover, in specification (2), LEP_k is statistically significant for all three different lagged values of *EP* with the coefficients of 0.0074, 0.0088, and 0.0073 and the t-statistics of 3.35, 3.96, and 3.39. In addition, there is no monotonic decrease or increase in LEP_k from k=36-months to k=60-months. The magnitudes and the corresponding t-statistics for EP_t and LEP_k also indicate that there is no guarantee for the power of recent news over older news. Moreover, in specification (2) the results indicate that the average values of dE_k+*MOM* and *MOM*-REV_k are statistically significant for all three lags of *EP*; and dE_k+REV_k is also statistically different from zero when k is 60-months. It means that decomposition variables have averagely different effects on expected returns in magnitude. However, the results for Equation (3.16) in specification (3) indicate that *MOM* ($b_3 = a_3 + a_1$) is the only decomposition variable that is statistically significant. As mentioned, this result also implies that not all of the slope estimates for the components of *EP* are equal to each other. In conclusion, the components of *EP* may help extract information about expected returns in *EP* alone and enhance future return estimates for all k-month lags of *EP* analyses. Additionally, it can be inferred that the predictability of momentum is more important than other components for the full sample of country indexes.

In Table 3.4, for the developed country indexes, in specification (2) EP_t is significant, while in specification (3) it is not significant. Moreover, LEP_k values are also statistically significant for all three different lags, but the results for EP_t and LEP_k are not enough to infer that the recent news is more important than older news. They have similar coefficients in magnitude varying from 0.0043 to 0.0055. In addition, in Equation (3.15) of specification (2), the average values of dE_k+*MOM* and *MOM*-REV_k are statistically different from zero for all three different lags of *EP*. It means that components are averagely different from each other in magnitude. Furthermore, in Equation (3.16) of specification (3), only the slope coefficient for *MOM* is statistically significant. Moreover, the positive significant slope coefficient for *MOM* means that *MOM* has a greater slope coefficient than *EP* in magnitude. Thus, the results show that for all three different time horizons, the components of *EP* reveal important information that is buried in *EP*. It is inferred that this information increases the predictability of expected returns.

The results for the emerging country indexes show that both EP_t and LEP_k are consistently significant. However, the results do not provide accurate relation between EP_t and LEP_k. Although none of the average values of the sums and difference between the monthly coefficients from Equation (3.15) are statistically significant for all different time horizons, the results for Equation (3.16) indicate that dE_k is the only component that is statistically significant and have a negative effect on expected returns for any lagged value of *EP*. Based on the decomposition steps, it can be referred that the coefficient for *dE* $(b_2 = a_2 - a_1)$ is smaller than the one for *EP* in magnitude. Therefore, it can be concluded that not all of the slope coefficients for *EP* components are equal to each other and at least one coefficient for the components of *EP* is statistically significant. As a result, it can be inferred that decomposition of *EP* does matter for the emerging country indexes for all three different lags of *EP*, which means that these components include different information about expected returns. Moreover, it is suggested that change in earnings is an important variable that provides more accurate estimates of expected returns.

In summary, for the full sample and emerging country indexes EP_t is statistically significant in the both regression equations in specifications (1) and (3); for the developed country indexes only in specification (3) for three different lags of *EP*. Moreover, there is no monotonic decrease or increase in LEP_k through k=36-months to k=60-months for all three samples. I can only infer that LEP_{48} is more relevant than LEP_{36} and LEP_{60} for the full sample and developed country indexes. Moreover, the analyses results show that decomposing *EP* into four independent components provides independent information that improves the estimates of expected returns for the full sample of country indexes as well as developed and emerging country indexes. The significance of *EP* decomposition is robust to for all three different time horizons. In addition, *MOM* is the only decomposition variable that is statistically significant for the full sample and developed country indexes while *dE* is also the only one for the emerging country indexes when all k-months lags of *EP* are used. Consistent with the results of Cakici et al. (2015), who studied decomposition of *BM* in Chinese markets; these results also suggest that investors consider important accounting information when making investment decisions, evaluating assets in emerging markets. In conclusion, it can be inferred that for the full sample and developed country indexes momentum effect and for the emerging country indexes change in earnings are important components of *EP* that unlocks the buried information in *EP*, which can be used in predicting future expected returns better.

3.7.3. Regional Country-Industry Indexes

The full sample of country-industry indexes is divided into six different regions, which are North America[14], Europe[15], Asia[16], South America[17], MENA[18], and Japan. Table 3.5 presents the results from the regressions of (3.14), (3.15), and (3.16) for each region from Panel A to F for three different time horizons. Regional analyses enable us to examine the validity of *EP* decomposition across different regions.

< Table 3.5 >

For North America, the log of EP_t is consistently insignificant when all three different time horizons are used. Moreover, the coefficients and the corresponding t-statistics for LEP_k are increasing through k=36-months to k=60-months and LEP_{60} becomes statistically significant (coefficient=0.0031 and t-stat=1.87). However, the results for EP_t and LEP_k are not enough to obtain the power of recent news over older news. Moreover, decomposition regression (3.15) in specification (2) results show that the average values of dE_k+*MOM* and *MOM*-REV_k (when k=36-, 48-, and 60-months) and dE_k+REV_k (when k=60-months) are statistically different from zero. In addition, according to Equation (3.16) in specification (3), *MOM* is the only component that is statistically significant for all three different lags of *EP*. When decomposition analyses are performed with 36-months lagged value of *EP*, dE_k is also statistically significant. These results imply that decomposition variables have different effects on expected returns on average. Moreover,

---

[14] Region 1: US, Canada.
[15] Region 2: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Norway, Portugal, Spain, Sweden, Switzerland, UK, Czech Republic, Hungary, Poland, Turkey.
[16] Region 3: Australia, Hong Kong, New Zealand, Singapore, China, India, Indonesia, Korea, Malaysia, Pakistan, Philippine, Russia, South Africa, Taiwan, Thailand, Vietnam.
[17] Region 4: Argentina, Brazil, Chile, Mexico.
[18] Region 5: Bahrain, Egypt, Israel, Kuwait, Morocco, Oman, Qatar, UAE.

it can be inferred that decomposition of *EP* does matter and momentum is an important variable in estimating expected returns for all three different time horizons of *EP*.

The results for Europe in Table 3.5 show that both EP_t and LEP_k are consistently significant and the coefficients with the corresponding t-statistics for EP_t is greater than the ones for LEP_k. It means that the recent news in *EP* is more important than the *k*-months prior news in *EP* in predicting expected returns. Moreover, all of the average values of the sums and difference in specification (2) are statistically different from zero. Furthermore, in Equation (3.16), *MOM* (when k=36-, 48-, and 60-months), REV_k (when *k*=36-, and 48-months), and dE_k (when *k*=60-months) are statistically significant. It means that for all three different time horizons the components of *EP* may capture different mixes of information about returns, thus, provides more accurate estimates of expected returns.

For the country-industry indexes in Asia, EP_t is statistically significant in specification (1) and specification (3) with *k*=36-months. On the other hand, LEP_{36} and LEP_{48} are significant and they are greater than EP_t in magnitude. Moreover, the coefficients and the corresponding t-statistics for LEP_k also decay from 36-months to 60-months (form coefficient of 0.0044 and t-stat=2.08 to 0.0029 and 1.34, respectively). These results prove the power of recent news over prior news of *EP*. In specification (2), the average values of dE_k+REV_k is consistently significant, and *MOM*-REV_k is also significant when 36- and 60-months lagged values of *EP* are used. In addition, the results of Equation (3.16) in specification (3) indicate that REV_k is the only significant component when *k* is 36- and 60-months. Therefore, there is at least one evidence to conclude that components may unlock information in *EP* that increase the predictability of expected returns for three different lags of *EP*.

In South America, both recent value and *k*-months lagged values of *EP* are statistically significant. Furthermore, none of the sums and difference in specification (2) is statistically different from zero for all three different lags of *EP*. Moreover, the coefficients for the components in Equation (3.16) are also statistically insignificant when 36- and 60-months lagged values of *EP* are used. On the other hand, the 48-months lagged value analysis results of Equation (3.16) show that components dE_k and *MOM* are significant. As a result, decomposing *EP* into its components generate independent information that increases the predictability of expected returns only when 48-months lagged value of *EP* is used.

The results for the country-industry indexes in MENA point out that EP_t and LEP_k are statistically significant only when 48-months lagged value of *EP* is used in the decomposition analyses. However, the comparison between their coefficients in magnitude are not enough to conclude that recent news is more relevant than older news. Moreover, in specification (2), for all three different time horizons there is at least one average value of sums and/or difference that is statistically different from zero. It shows that on average decomposition variables generate different effects on expected returns. Additionally, according to the results of Equation (3.16) in specification (3), components of REV_k when k is 36-months; *MOM* when k is 48- and 60-months are statistically significant. In conclusion, it can be suggested that components of *EP* include independent information that provides increase in the estimates of expected returns for all three different lags of *EP*. Moreover, momentum and reversal effects have more predictive power in estimating returns.

Lastly, in Japan, regression results for EP_t show that it is statistically significant both in specification (1) and specification (3) except when k=36-months. On the other hand, LEP_{48} and LEP_{60} are statistically significant and their coefficients are slightly smaller than the one for EP_t. Moreover, only dE_k+MOM is statistically different from zero in specification (2). The results of Equation (3.16) in specification (3) show that *MOM* is the only component that is significant when 48- and 60-months lagged values of *EP* are used. On the other hand, even if there is no significant component in specification (3) for 36-months lagged value analyses, dE_k+MOM is statistically significant in specification (2). As a result, it can be concluded that components of *EP* contain information about returns that may improve the future return estimates for the decomposition analyses with three different lags of *EP*.

In summary, EP_t is statistically significant at least in one regression equation for all three different lags of *EP* in Europe, Asia, South America, MENA, and Japan. On the other hand, EP_t is insignificant for all three lags of *EP* in North America. This implies that decomposing *EP* is important for North America to extract the additional information about future expected returns. In addition, there is no monotonic decrease or increase in LEP_k for all regions, except Asia. Unlike these regions, there is a monotonic decrease in LEP_k for Asia implying that recent news buried in *EP* is more important than older news in predicting returns. Moreover, *MOM* is generally significant for all regions and for all three different lags of *EP*, except Asia. Differently, in Asia, REV_k is the only component that is significant when LEP_{36} and LEP_{60} are used. Moreover, dE_k and REV_k are also significant depending on the region and lag of the *EP*. Consequently, the analyses results show that decomposing *EP* into four independent components increases the estimates of expected returns for all three different lags of *EP* for the country-industry indexes in the regions of North America, Europe, Asia, MENA, and Japan. Additionally, in South America, decomposition of *EP* does matter only when 48-months lagged value of *EP* is used.

3.7.4. Size Portfolios of Country-Industry Indexes

The country-industry indexes are divided into quintile portfolios based on the market capitalization values to investigate the significance of *EP* decomposition across size portfolios. Firstly, the country-industry indexes are sorted based on the previous month's market capitalization value and thereafter, quintile portfolios are formed every month in the sample period. Portfolio *MV*1 includes the industry indexes with the lowest market capitalizations while portfolio *MV*5 includes those with the highest market capitalizations. For each size portfolio, *EP* decomposition analyses are performed for each month. Table 3.6 shows the average results of Fama-MacBeth regressions for each size portfolio from Panels A to E. The analyses are also performed for the different lags of *EP*, which are 36-, 48-, and 60-months.

< Table 3.6 >

In Table 3.6, for the country-industry indexes in portfolio *MV*1 both EP_t and LEP_k values are statistically insignificant for all three different lags of *EP*. Therefore, the results for EP_t and LEP_k give no accurate inference about the relation between recent and distant news. Moreover, in specification (2), all of the average values of the sums and difference between monthly coefficients from Equation (3.15) and in specification (3), the components of *MOM* and REV_k from Equation (3.16) are statistically significant. It means that components of *EP* affect expected returns differently in magnitude. As a result, there is at least one evidence for the validity of decomposition of *EP* and components reveal different information about expected returns.

In the portfolio *MV*2, the magnitude of the coefficient for EP_t is less than the one for LEP_k for each lag of *EP*, respectively. For this reason, the inference of being recent news more powerful than older news is failure. Moreover, the average values of all the sums and difference between the coefficients from Equation (3.15) in specification (2) and the coefficient for *MOM* in Equation (3.16) are statistically different from zero for all lags of *EP*. In addition, REV_k is also significant when LEP_{48} and LEP_{60} are used. It implies that using the components instead of *EP* captures different mixes of information and enhances estimates of expected returns for three different time horizons of *EP*.

The significant results of both recent value and *k*-months prior value of *EP* point out that *k*-months news is more important than recent news for the portfolio *MV*3. Furthermore, similar with portfolio *MV*1 and *MV*2, the average values of all the sums and difference in specification (2) and the component of *MOM* in specification (3) are significant for all *k*-months analyses. Additionally, dE_k is also significant when 36-months lagged value of *EP* is used. Consequently, decomposing *EP* into three components generates independent information that increases the predictability of future returns for all *k*-months lagged analyses.

For the country-industry indexes in the portfolio *MV*4, EP_t (when *k*=48-months) and LEP_k (when *k*=36- and 48-months) are statistically significant. The results provide no evidence about the relation between recent and distant news. In addition, in specification (2) dE_k+MOM and $MOM-REV_k$; in specification (3) the component *MOM* are statistically different from zero for all *k*-months analyses. As a result, it can be suggested that decomposition of *EP* does matter and momentum is an important variable in estimating returns.

Lastly, in the portfolio *MV*5, the insignificant results of EP_t and LEP_k give no guarantee about the power of recent news over distant news. Moreover, in specification (2), the average values of dE_k+MOM and $MOM-REV_k$ for three different *k*-months lagged analyses and dE_k+REV_k for 60-months lagged analyses are statistically different from zero. Additionally, in specification (3), the components of *MOM* for all lags and REV_k for 60-months lag are significant. In conclusion, the effect of the components still exists across the country-industry indexes that have high market capitalization values. The components include independent information that provide more accurate estimates of expected returns. Additionally, momentum and reversal effects have more predictive powers in estimating returns.

In summary, for the portfolios *MV*2 and *MV*3 both EP_t and LEP_k are statistically significant for all *k*-months lagged analyses. On the other hand, for the portfolios *MV*1 and *MV*5 both EP_t and LEP_k are consistently insignificant for all three different lags of *EP*. In addition, there is a significant monotonic decrease in LEP_k from *k*=36-months to *k*=60-months for the portfolios *MV*2 and *MV*4, which implies the power of recent news over older news. Moreover, the results for specification (2) show that for the portfolios *MV*1, *MV*2, and *MV*3 all of the average values of the difference/summations (for all *k*-months analyses); for the portfolios *MV*4 and *MV*5 both dE_k+*MOM* and *MOM*-REV_k (for all *k*-months analyses); and for the portfolio *MV*5 dE_k+REV_k (for 60-months analysis) are statistically different from zero. These results imply that on average components of *EP* have different effects on expected returns in magnitude. Furthermore, in specification (3), the component of *MOM* is consistently significant for all size portfolios and for all three different lags of *EP*. Additionally, REV_k is significant for the portfolio *MV*1 (for all *k*-months analyses), *MV*2 (for 48- and 60-months analyses), *MV*5 (for 60-months analysis); and dE_k is statistically significant for the portfolio *MV*3 (for 36-months analysis). The number of significant components decreases from portfolio *MV*1 to *MV*5, which can be inferred as the portfolios with the highest market capitalization values, the decomposition analyses reveals less information than other portfolios with lower market capitalization values. In conclusion, the results point out that breaking *EP* into its components unlocks the buried information in *EP* alone and increases the estimates of expected returns for all the size quintiles and three different lags of *EP*[19].

[19] Alternatively, sub-sample effects can be examined by including the interaction terms in regressions analyses. However, this can further complicate the interpretation of so many coefficient estimates.

3.7.5. Size Portfolios of Country Indexes

EP decomposition analyses are also performed for the size portfolios of country indexes including 51 countries. Similarly, the country indexes are sorted based on the previous month's market capitalization values and thus, three size portfolios are formed every month. As a result, portfolio *MV*1 includes the country indexes with the lowest market capitalizations while portfolio *MV*3 includes the country indexes with the highest market capitalizations. The Fama-MacBeth regressions are estimated for each size portfolio every month in the sample period. The results for the three different lags of *EP*, which are 36-, 48-, and 60-months are shown in Table 3.7.

< Table 3.7 >

For the country indexes having smallest market capitalization values in the portfolio *MV*1, the coefficient EP_t is only significant when decomposition analysis is made with 60-months lagged value of *EP*. On the other hand, LEP_k values are significant for all *k*-months lagged analyses and their coefficient with the corresponding t-statistics are greater than the ones for EP_t. Moreover, according to the results of Equation (3.15) in specification (2), none of the average values of the difference/summations is statistically different from zero. However, in Equation (3.16), dE_k is consistently significant for all *k*-months lagged analyses, which implies that components have different effects on expected return on average. Almost similar with the results of Table 3.4, for the stock markets that have lower market capitalization values (also referred as emerging markets) accounting information is important when making investment decisions, which is also in line with the results of Cakici et al. (2015). In conclusion, decomposing *EP* helps extract information in *EP* to enhance estimates of expected returns for country indexes that have lower market capitalization values for all three lags of *EP*.

In the portfolio *MV*2, since the coefficients for EP_t in specification (3) are less than the ones for LEP_k in specification (2), the power of recent news over older news is failure for all three lags of *EP*. Moreover, although none of the average values of the sums and difference is significant for the coefficients from Equation (3.15) in specification (2), REV_k when k=36-months; both dE_k and *MOM* when k=48-months are statistically significant in specification (3). It implies that not all of the slope estimates for the components are equal to each other for the analyses with 36- and 48-months lags. Therefore, it can be inferred that decomposition of *EP* does matter when 36-months and 48-months lagged values of *EP* are used.

For the country indexes having highest market capitalization values in the portfolio *MV*3, EP_t is only significant in specification (1) and LEP_k values are consistently insignificant in specification (2). According to the results of specification (2), none of the sums and difference is statistically different from zero based on the coefficients from Equation (3.15). However, in Equation (3.16), components of dE_k and REV_k are statistically significant for the analyses with 60-months lagged value of *EP*. The results point out that decomposition of *EP* is valid only when 60-months prior value of *EP* is used. Additionally, both change in earnings and reversal effect play powerful roles in predicting future returns.

In summary, EP_t is statistically significant in specification (3) for the portfolio *MV*1 (when *k*=60-months); in specification (1) for the portfolio *MV*3; in both specifications for the portfolio *MV*2 (for all *k*-months lags of *EP*). Moreover, while LEP_k values are statistically significant for the portfolios *MV*1 and *MV*2 for all three lags of *EP*, it is consistently insignificant for the portfolio *MV*3. These results give no accurate inference about the power of recent news over distant news. Furthermore, for all size portfolios, in specification (2), none of the average values of sums and difference between the monthly coefficients from Equation (3.15) is statistically different from zero for all *k*-months lagged values of *EP*. Additionally, dE_k is statistically significant for the portfolios *MV*1 (for all *k*-months analyses), *MV*2 (for 48-months analysis), and *MV*3 (for 60-months analysis). Also, the components of *MOM* for the portfolio *MV*2 (for 48-months analysis) and REV_k for the portfolios *MV*2 (for 36-months analysis) and *MV*3 (for 60-months analysis) are statistically significant. The results from portfolio *MV*1 to *MV*3 point out that the lower the market capitalization of the portfolio, the higher the number of components that is significant. Therefore, it can be inferred that in the lower market capitalization portfolios, decomposition of *EP* may capture more mixes of information in *EP* alone for country indexes. Consistent with the previous results and the study of Cakici et al. (2015), it can be inferred that accounting information is important when making investment decisions in portfolios with low market capitalization values. Consequently, decomposition of *EP* does matter for size portfolios *MV*1 (for all *k*-months lags of *EP*), *MV*2 (for 36-months and 48-months lags of *EP*), and *MV*3 (for 60-months lag of *EP*).

3.8. Conclusion

In this dissertation chapter, in the sense of Fama and French (2008), who decomposed the *BM* ratio at the stock level, I examine the value effect by decomposing the *EP* ratio into four independent components: lagged *EP* value, change in earnings, momentum, and reversal. I investigate whether these components can be used to extract buried information to estimate future returns better than the *EP* ratio alone. The decomposition analyses are performed for the full sample as well as developed and emerging sub-samples of country-industry and country indexes by using 51 country indexes and 19 different *supersector* indexes from January 1973 to July 2017. In addition, the analyses are also performed for regions by separating country-industry indexes into six different regions and for size portfolios of country-industry and country indexes. I also use three different time horizons for lagged value of *EP*, which are 36-, 48-, and 60-months lags.

The results for country-industry indexes show that a significant earnings-to-price ratio effect exists for the full and developed samples for all three different lags of *EP*. On the other hand, for the emerging sample the significant effect of *EP* reduces and changes depending on the lags of *EP* used. Moreover, decomposing *EP* into its components reveals information that provides more accurate estimates of expected returns for all *k*-months lags of *EP* for the full and developed samples of country-industry indexes and for 36-months and 60-months lags of *EP* for emerging sample of country-industry indexes. Furthermore, the results for country indexes (for the full, developed, and emerging samples) point out that there is a significant *EP* effect and the components of *EP* include independent information that can be used to improve estimates of future returns for all three different lags of *EP*. In addition, in general there are quite momentum and a little reversal effects for country-industry indexes. Moreover, for country indexes (both full and developed samples) momentum affects expected returns significantly. However, for the emerging sample of country indexes there is a significant change in earnings effect, which means that accounting information is more important for investors when making investment decisions in emerging markets.

Regional analyses results point out that the components of *EP* also have an important effect on expected returns depending on the lags of *EP* and regions. In general, decomposition of *EP* does matter for North America, Europe, Asia, MENA, and Japan when all *k*-months lagged values of *EP* are used. However, there is no evidence that components of *EP* increase the predictability of expected returns for South America when decomposition analyses are performed with 36-months and 60-months lags of *EP*.

Size portfolio analyses of country-industry indexes generally show that for the portfolios that includes the indexes with low market capitalization values, the component of *EP* reveals much more information buried in *EP* alone and enhance the future return estimates. Moreover, decomposition of *EP* is valid for all size portfolios of country-industry indexes for all three different lags of *EP*. Similarly, when size portfolio analyses are performed for country indexes, components of *EP* increase the predictability of expected returns generally for the country indexes with low market capitalization values. On the other hand, when the market capitalization values increase, the validity of decomposition of *EP* decreases depending on the lags of *EP* used in the regression. Additionally, similar with the analyses in local stock market indexes, there is a significant change in earnings effect for the country indexes with low market capitalization values and the change in earnings effect decreases through the portfolio that includes the country indexes with high market capitalization values.

Lastly, the results unable us to infer that the recent news is more relevant than the older news in general. In some cases, for a specific lagged value of *EP*, the results provide evidence that the recent news is more powerful than older news in explaining future expected returns on emerging country indexes and country-industry indexes of Europe and Asia.

In general, the results show that decomposing *EP* into four independent components may reveal additional information about expected returns, thus, improves the estimates of expected returns as well as for international indexes. For the country-industry and country indexes, the significance of *EP* decomposition changes across sub-samples of developed and emerging markets, size portfolios, regions, and for different time horizons. These results can be beneficial for international investors, who aim to diversify their portfolios across regions as well as developed and emerging markets.

3.9. Tables

Table 3.1. Basic Statistics for Supersector Indexes

This table provides the basic statistics for the supersectors, which are used to track industry indexes. First, the value-weighted cross-sectional averages of excess returns on each industry index is calculated across 51 countries every month in the whole research period. Then, the time-series averages of cross-sectional means over the months in the sample are calculated. *Return*. *Max*, *Min*, *Std.Dev.* show the maximum, minimum, and standard deviation of the cross-sectional means of industry returns over the months. In addition, *N* is the total number of observations; *MV* is the average market capitalization in $US billions; *PE* is the average price-to-earnings ratio; *DY* is the average dividend yield of each industry. End date for monthly series is July 2017. Start date changes across local supersectors. The earliest start date is January 1973 for the monthly series.

Supersector	*N*	*Return*(%)	*Max*	*Min*	*Std.Dev.*	*MV*	*PE*	*DY*
Automobile & Parts	9990	0.69	0.2066	-0.2255	0.0538	22.68	19.97	0.0315
Banks	17721	0.88	0.3202	-0.2490	0.0583	50.59	21.00	0.0355
Basic Resource	14864	0.85	0.3260	-0.3112	0.0683	18.85	30.19	0.0316
Chemicals	14939	0.79	0.1851	-0.2056	0.0517	14.43	34.55	0.0342
Construction & Mat.	17544	0.84	0.1958	-0.2339	0.0565	8.97	18.93	0.0310
Financial Services	15524	0.95	0.3173	-0.2356	0.0646	24.07	30.91	0.0330
Food & Beverages	17175	0.82	0.2172	-0.1479	0.0412	19.99	21.93	0.0297
Health Care	15689	0.73	0.2059	-0.1551	0.0406	53.68	30.05	0.0290
Inds. Goods & Svs.	18648	0.73	0.1624	-0.2107	0.0490	48.34	28.45	0.0302
Insurance	14922	0.86	0.1878	-0.2433	0.0512	22.88	26.79	0.0289
Media	11923	0.58	0.2079	-0.2057	0.0527	16.47	25.51	0.0260
Oil & Gas	15029	0.82	0.2098	-0.2007	0.0555	43.70	19.65	0.0325
Pers. & H/H Goods	14228	0.73	0.1777	-0.1876	0.0444	27.96	23.29	0.0311
Real Estate	14378	1.05	0.2987	-0.2424	0.0635	12.63	45.46	0.0331
Retail	14915	0.73	0.2315	-0.1909	0.0501	22.24	21.35	0.0273
Technology	11511	0.77	0.2436	-0.2579	0.0647	57.12	32.07	0.0200
Telecom	14471	0.80	0.4750	-0.1686	0.0521	31.92	31.35	0.0306
Travel & Leisure	14646	0.98	0.3619	-0.2704	0.0580	9.55	27.09	0.0247
Utilities	13633	0.75	0.2660	-0.1376	0.0431	26.19	17.40	0.0396

Table 3.2. Basic Statistics for Country Indexes

This table shows the basic statistics for the local stock market indexes of 51 countries, which 23 are developed and 28 are emerging. *N* is the number of monthly observations; *Return* is the value-weighted average monthly excess return. *Max, Min, Std.Dev.* are the time-series statistics for monthly country index returns. *MV* is the average market capitalization in $US billions; *PE* is the average price-to-earnings ratio; *DY* is the average dividend yield of each industry. End date for monthly series is July 2017. Start date changes across countries. The earliest start date is January 1973 for the monthly series. Panel A (B) reports the results for the developed (emerging) markets.

Panel A: Developed Markets

Country	*N*	*Return*(%)	*Max*	*Min*	*Std.Dev.*	*MV*	*PE*	*DY*
Australia	534	0.67	0.2227	-0.3875	0.0705	393.23	15.04	0.0410
Austria	534	0.58	0.3403	-0.3159	0.0663	43.15	17.08	0.0206
Belgium	534	0.64	0.2409	-0.3036	0.0582	124.24	14.02	0.0362
Canada	533	0.50	0.2251	-0.2525	0.0548	588.20	15.81	0.0302
Denmark	533	0.77	0.2165	-0.2459	0.0587	86.96	17.43	0.0195
Finland	351	0.83	0.3636	-0.2746	0.0842	133.96	15.75	0.0306
France	534	0.75	0.2620	-0.2706	0.0664	768.41	13.81	0.0369
Germany	534	0.58	0.1994	-0.2015	0.0598	671.56	15.23	0.0266
Greece	330	0.39	0.5734	-0.3126	0.1071	57.30	15.43	0.0267
Hong Kong	534	1.01	0.7979	-0.4636	0.0971	536.34	14.34	0.0356
Ireland	534	0.74	0.4422	-0.2578	0.0703	38.64	13.09	0.0359
Italy	534	0.50	0.2767	-0.2381	0.0753	316.65	17.81	0.0295
Japan	534	0.40	0.2443	-0.2353	0.0612	2405.20	34.02	0.0138
Netherland	534	0.70	0.2673	-0.2904	0.0560	297.87	13.56	0.0401
New Zealand	353	0.73	0.2670	-0.1932	0.0629	30.45	15.90	0.0462
Norway	449	0.77	0.2453	-0.3030	0.0788	97.39	12.11	0.0287
Portugal	329	0.30	0.2923	-0.2496	0.0632	54.29	17.46	0.0340
Singapore	534	0.61	0.5798	-0.3483	0.0819	152.28	18.42	0.0269
Spain	364	0.68	0.2358	-0.2209	0.0668	414.15	14.98	0.0355
Sweden	425	1.00	0.2221	-0.2245	0.0715	241.02	16.93	0.0277
Switzerland	534	0.66	0.2118	-0.1751	0.0516	485.18	14.93	0.0230
UK	534	0.62	0.5239	-0.2188	0.0623	1466.61	13.95	0.0414
USA	533	0.55	0.1712	-0.2154	0.0453	7507.45	16.64	0.0292

Table 3.2. Basic Statistics for Country Indexes (cont.)

Panel B: Emerging Markets								
Country	*N*	*Return*(%)	*Max*	*Min*	*Std.Dev.*	*MV*	*PE*	*DY*
Argentina	287	0.72	0.3848	-0.3050	0.0955	30.10	22.71	0.0315
Bahrain	162	0.28	0.1214	-0.1137	0.0371	18.81	11.16	0.0447
Brazil	275	0.99	0.3435	-0.2976	0.1014	523.88	12.34	0.0346
Chile	336	1.05	0.2146	-0.2300	0.0659	107.57	16.83	0.0352
China	287	1.13	0.4235	-0.2448	0.0992	264.64	10.72	0.0337
Czech Republic	283	0.95	0.7064	-0.2801	0.0874	27.38	14.82	0.0434
Egypt	249	0.67	0.3654	-0.3416	0.0877	36.72	13.78	0.0442
Hungary	312	1.01	0.8366	-0.3778	0.1059	17.23	16.33	0.0300
India	330	1.08	0.5471	-0.3343	0.1017	482.09	18.99	0.0142
Indonesia	327	1.36	0.9994	-0.5044	0.1744	119.26	16.82	0.0213
Israel	294	0.58	0.1958	-0.2043	0.0666	79.96	12.01	0.0306
Korea	357	0.82	0.4969	-0.3381	0.1015	385.63	15.42	0.0169
Kuwait	162	0.39	0.1632	-0.2002	0.0557	86.77	15.80	0.0372
Malaysia	377	0.83	0.4481	-0.3454	0.0819	159.40	18.21	0.0288
Mexico	337	1.15	0.2489	-0.3458	0.0819	198.71	14.69	0.0195
Morocco	279	0.88	0.2659	-0.1305	0.0487	31.66	18.21	0.0351
Oman	141	0.53	0.1706	-0.2189	0.0490	18.04	10.98	0.0481
Pakistan	299	0.89	0.3134	-0.4496	0.0922	24.16	12.25	0.0483
Philippine	357	0.91	0.5229	-0.2716	0.0839	68.38	17.59	0.0151
Poland	280	0.53	0.3786	-0.3565	0.1033	75.50	15.20	0.0240
Qatar	162	1.05	0.4864	-0.2482	0.0870	109.34	16.05	0.0334
Russia	233	1.46	0.5750	-0.6342	0.1284	411.98	9.22	0.0233
South Africa	534	0.82	0.3213	-0.3437	0.0822	148.13	12.78	0.0392
Taiwan	350	0.69	0.5212	-0.3743	0.1006	300.65	23.15	0.0242
Thailand	365	1.13	0.5136	-0.3297	0.1010	105.14	14.64	0.0311
Turkey	353	1.53	0.6602	-0.4231	0.1547	92.89	13.19	0.0342
UAE	162	1.17	0.3612	-0.2246	0.0840	138.33	13.53	0.0324
Vietnam	122	0.16	0.2763	-0.2527	0.0826	30.96	15.64	0.0294

Table 3.3. Cross-Sectional Regressions for Country-Industry Indexes

This table presents the averages of the slope coefficients from the cross-sectional regressions of Equations (3.14), (3.15), and (3.16), which regress previous month's country-industry index returns on *EP* and its components from January 1973 to July 2017. The results are shown for the full sample of country-industry indexes in Panel A, as well as developed and emerging country-industry indexes in Panel B and C, respectively. *EP* is the log of the earnings-to-price ratio at month *t-1*; LEP_k is the log of *EP* value at month *t-k*; dE_k is the log of the change in the earnings from month *t-k* to *t-1*; *MOM* is the cumulative log of the return from *t-12* to *t-1*; and REV_k is the cumulative log of the return from month *t-k* to *t-12*. *k* represents the distance in months to present for computing long-term *EP*. dE_k+*MOM*, dE_k+REV_k, and *MOM*-REV_k show the monthly average values of sums and difference between the coefficient estimates of dE_k, *MOM*, and REV_k from regression Equation (3.15). The Newey-West (1987) adjusted *t*-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Full Sample

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0172***	0.0029***								0.0165
		(4.99)	(2.93)								
(2)	k=36	0.0174***		0.0036***	0.0028***	0.0091***	-0.0067***	0.0118***	-0.0040***	0.0158***	0.0875
		(4.33)		(3.33)	(3.12)	(2.76)	(-4.60)	(3.59)	(-2.89)	(4.74)	
	k=48	0.0183***		0.0038***	0.0028***	0.0088***	-0.0060***	0.0116***	-0.0033***	0.0148***	0.0879
		(4.72)		(3.39)	(3.30)	(2.76)	(-3.93)	(3.57)	(-2.59)	(4.53)	
	k=60	0.0178***		0.0036***	0.0026***	0.0086***	-0.0062***	0.0112***	-0.0036***	0.0148***	0.0878
		(4.68)		(3.61)	(3.02)	(2.70)	(-4.40)	(3.51)	(-3.20)	(4.59)	
(3)	k=36	0.0165***	0.0034***		-0.0007	0.0125***	-0.0032**				0.0878
		(4.27)	(3.29)		(-1.24)	(3.87)	(-2.22)				
	k=48	0.0173***	0.0036***		-0.0009	0.0124***	-0.0024				0.0884
		(4.65)	(3.38)		(-1.60)	(3.95)	(-1.56)				
	k=60	0.0169***	0.0035***		-0.0009*	0.0120***	-0.0027**				0.0884
		(4.67)	(3.70)		(-1.92)	(3.82)	(-2.13)				

Table 3.3. Cross-Sectional Regressions for Country-Industry Indexes (cont.)

Panel B: Developed Markets

		α_0	EP	LEP_k	dE_k	MOM	REV_k	dE_k+MOM	dE_k+REV_k	MOM-REV_k	R^2
(1)		0.0142***	0.0020								0.0247
		(3.21)	(1.51)								
(2)	k=36	0.0135***		0.0026**	0.0022***	0.0126***	-0.0054***	0.0148***	-0.0032*	0.0180***	0.1109
		(3.19)		(2.25)	(2.63)	(3.34)	(-2.91)	(3.97)	(-1.94)	(4.78)	
	k=48	0.0147***		0.0027**	0.0023***	0.0119***	-0.0049***	0.0142***	-0.0026*	0.0168***	0.1106
		(3.40)		(2.28)	(2.73)	(3.20)	(-2.66)	(3.88)	(-1.70)	(4.60)	
	k=60	0.0143***		0.0026**	0.0020**	0.0118***	-0.0047***	0.0138***	-0.0027**	0.0165***	0.1101
		(3.22)		(2.25)	(2.38)	(3.11)	(-2.88)	(3.77)	(-2.10)	(4.55)	
(3)	k=36	0.0132***	0.0026**		-0.0004	0.0152***	-0.0027*				0.1113
		(3.24)	(2.32)		(-0.62)	(4.45)	(-1.69)				
	k=48	0.0142***	0.0027**		-0.0003	0.0145***	-0.0022				0.1112
		(3.48)	(2.36)		(-0.49)	(4.32)	(-1.36)				
	k=60	0.0138***	0.0026**		-0.0006	0.0143***	-0.0021				0.1108
		(3.29)	(2.34)		(-0.87)	(3.99)	(-1.61)				

Panel C: Emerging Markets

		α_0	EP	LEP_k	dE_k	MOM	REV_k	dE_k+MOM	dE_k+REV_k	MOM-REV_k	R^2
(1)		0.0351***	0.0099***								0.1196
		(3.86)	(2.71)								
(2)	k=36	0.0188**		0.0037	0.0030**	0.0013	-0.0059***	0.0043	-0.0030	0.0073*	0.1431
		(2.31)		(1.30)	(2.05)	(0.32)	(-3.05)	(0.96)	(-1.50)	(1.76)	
	k=48	0.0050		-0.0006	-0.0015	-0.0001	0.0016	-0.0015	0.0002	-0.0017	0.1443
		(0.54)		(-0.25)	(-0.76)	(-0.01)	(0.42)	(-0.33)	(0.04)	(-0.27)	
	k=60	0.0094		0.0055***	0.0164	0.0051	-0.0118**	0.0215*	0.0046	0.0169***	0.1421
		(1.29)		(2.85)	(0.84)	(1.31)	(-2.18)	(1.74)	(0.64)	(3.08)	
(3)	k=36	0.0109	0.0009		0.0015	0.0022	-0.0034				0.1431
		(1.51)	(0.38)		(0.61)	(0.39)	(-0.79)				
	k=48	0.0051	-0.0005		-0.0001	-0.0005	-0.00004				0.1446
		(0.55)	(-0.22)		(-0.04)	(-0.09)	(-0.02)				
	k=60	0.0139**	0.0086***		0.0121	0.0180***	-0.0076				0.1421
		(2.25)	(4.40)		(0.74)	(3.96)	(-0.99)				

Table 3.4. Cross-Sectional Regressions for Country Indexes

This table presents the averages of the slope coefficients from the cross-sectional regressions of Equations (3.14), (3.15), and (3.16), which regress previous month's country index returns on *EP* and its components from January 1973 to July 2017. The results are shown for the full sample of country-industry indexes in Panel A, as well as developed and emerging country-industry indexes in Panel B and C, respectively. All variables are as explained before (*EP*, LEP_k, dE_k, *MOM*, REV_k, dE_k+MOM, dE_k+REV_k, $MOM\text{-}REV_k$). The Newey-West (1987) adjusted *t*-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Full Sample

		α_0	EP	LEP_k	dE_k	MOM	REV_k	dE_k+MOM	dE_k+REV_k	$MOM\text{-}REV_k$	R^2
(1)		0.0225***	0.0053***								0.0576
		(4.01)	(3.23)								
(2)	k=36	0.0271***		0.0074***	0.0041	0.0061	-0.0057*	0.0102*	-0.0016	0.0118**	0.2712
		(3.31)		(3.35)	(1.39)	(1.26)	(-1.67)	(1.89)	(-0.59)	(2.13)	
	k=48	0.0313***		0.0088***	0.0040	0.0069	-0.0066**	0.0109**	-0.0026	0.0135**	0.2727
		(3.90)		(3.96)	(1.37)	(1.40)	(-1.96)	(2.02)	(-1.20)	(2.47)	
	k=60	0.0267***		0.0073***	0.0041	0.0059	-0.0080**	0.0100*	-0.0039*	0.0139***	0.2724
		(3.31)		(3.39)	(1.52)	(1.20)	(-2.53)	(1.93)	(-1.90)	(2.66)	
(3)	k=36	0.0214***	0.0057***		-0.0022	0.0120***	0.0008				0.2708
		(2.71)	(2.74)		(-0.74)	(2.66)	(0.25)				
	k=48	0.0259***	0.0072***		-0.0039	0.0145***	0.0015				0.2715
		(3.45)	(3.59)		(-1.31)	(3.05)	(0.42)				
	k=60	0.0199***	0.0053***		-0.0022	0.0112**	-0.0016				0.2715
		(2.66)	(2.77)		(-0.95)	(2.41)	(-0.65)				

Table 3.4. Cross-Sectional Regressions for Country Indexes (cont.)

Panel B: Developed Markets											
		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0165**	0.0033								0.0929
		(2.25)	(1.45)								
(2)	k=36	0.0192***		0.0047**	0.0017	0.0117**	-0.0028	0.0134**	-0.0011	0.0145***	0.3624
		(2.78)		(2.33)	(0.55)	(2.46)	(-0.70)	(2.55)	(-0.32)	(2.67)	
	k=48	0.0221***		0.0055***	0.0009	0.0152***	-0.0038	0.0161***	-0.0029	0.0190***	0.3565
		(3.45)		(3.00)	(0.29)	(2.92)	(-1.11)	(2.82)	(-1.07)	(3.68)	
	k=60	0.0191**		0.0046**	0.0030	0.0116**	-0.0067*	0.0146***	-0.0035	0.0181***	0.3665
		(2.48)		(2.07)	(1.24)	(2.05)	(-1.85)	(2.58)	(-1.34)	(3.18)	
(3)	k=36	0.0185***	0.0047**		-0.0029	0.0164***	0.0020				0.3639
		(2.93)	(2.48)		(-0.93)	(3.92)	(0.54)				
	k=48	0.0210***	0.0054***		-0.0044	0.0205***	0.0016				0.3583
		(3.57)	(3.13)		(-1.64)	(4.36)	(0.56)				
	k=60	0.0179***	0.0043**		-0.0012	0.0154***	-0.0023				0.3679
		(2.62)	(2.19)		(-0.57)	(2.92)	(-0.94)				

Panel C: Emerging Markets											
		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0360***	0.0092**								0.0797
		(2.91)	(2.54)								
(2)	k=36	0.0489***		0.0161***	0.0068*	-0.0081	-0.0091*	-0.0013	-0.0023	0.0009	0.3164
		(2.72)		(2.79)	(1.67)	(-0.92)	(-1.77)	(-0.18)	(-0.55)	(0.11)	
	k=48	0.0569***		0.0184***	0.0079**	-0.0098	-0.0130**	-0.0020	-0.0051	0.0031	0.3166
		(3.72)		(3.92)	(1.99)	(-1.23)	(-2.46)	(-0.24)	(-1.59)	(0.40)	
	k=60	0.0585***		0.0188***	0.0092	-0.0081	-0.0144***	0.0010	-0.0053	0.0063	0.3065
		(2.94)		(2.60)	(1.46)	(-0.95)	(-2.60)	(0.13)	(-1.32)	(0.77)	
(3)	k=36	0.0294*	0.0091**		-0.0060**	0.0020	0.0025				0.3158
		(1.95)	(2.03)		(-2.19)	(0.25)	(0.63)				
	k=48	0.0406***	0.0132***		-0.0079***	0.0053	0.0026				0.3150
		(3.00)	(3.31)		(-3.38)	(0.64)	(0.57)				
	k=60	0.0368***	0.0116***		-0.0063**	0.0045	0.0005				0.3062
		(2.65)	(2.60)		(-2.44)	(0.56)	(0.19)				

Table 3.5. Cross-Sectional Regressions for Regions of Country-Industry Indexes

This table presents the averages of the slope coefficients from the cross-sectional regressions of Equations (3.14), (3.15), and (3.16), which regress previous month's country-industry index returns on *EP* and its components for six different regions. Panels A to F present the results for the regions of North America, Europe, Asia, South America, MENA, and Japan, respectively. All variables are as explained before (EP, LEP_k, dE_k, MOM, REV_k, dE_k+MOM, dE_k+REV_k, MOM-REV_k). The Newey-West (1987) adjusted *t*-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: North America

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0121**	0.0016								0.0667
		(2.26)	(0.86)								
(2)	k=36	0.0083		0.0012	0.0031**	0.0141***	-0.0051	0.0172***	-0.0020	0.0192***	0.2898
		(1.40)		(0.77)	(1.97)	(3.00)	(-1.34)	(3.67)	(-0.61)	(3.77)	
	k=48	0.0122**		0.0026	0.0022*	0.0159***	-0.0053	0.0180***	-0.0032	0.0212***	0.2925
		(2.10)		(0.53)	(1.66)	(3.31)	(-1.64)	(3.90)	(-1.24)	(3.90)	
	k=60	0.0139**		0.0031*	0.0017	0.0149***	-0.0054**	0.0166***	-0.0038*	0.0203***	0.2886
		(2.50)		(1.87)	(1.16)	(3.34)	(-1.96)	(3.92)	(-1.87)	(4.51)	
(3)	k=36	0.0067	0.0006		0.0022*	0.0150***	-0.0040				0.2917
		(1.25)	(0.41)		(1.76)	(3.18)	(-1.18)				
	k=48	0.0092*	0.0015		0.0002	0.0180***	-0.0031				0.2931
		(1.78)	(1.01)		(0.14)	(3.87)	(-1.08)				
	k=60	0.0104**	0.0019		-0.0008	0.0175***	-0.0028				0.2899
		(2.11)	(1.24)		(-0.69)	(3.96)	(-1.27)				

Table 3.5. Cross-Sectional Regressions for Regions of Country-Industry Indexes (cont.)

Panel B: Europe

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0165***	0.0028**								0.0207
		(4.07)	(2.41)								
(2)	k=36	0.0155***		0.0031**	0.0032***	0.0107***	-0.0089***	0.0140***	-0.0057***	0.0197***	0.1072
		(3.77)		(2.53)	(4.26)	(3.08)	(-4.25)	(4.41)	(-2.99)	(5.11)	
	k=48	0.0190***		0.0041***	0.0034***	0.0100***	-0.0075***	0.0134***	-0.0040**	0.0175***	0.1038
		(4.76)		(3.71)	(4.65)	(2.83)	(-3.94)	(4.17)	(-2.40)	(4.86)	
	k=60	0.0190***		0.0041***	0.0031***	0.0099***	-0.0062***	0.0130***	-0.0031**	0.0161***	0.1041
		(5.12)		(4.75)	(4.18)	(2.78)	(-3.99)	(4.05)	(-2.43)	(4.73)	
(3)	k=36	0.0155***	0.0033***		0.00002	0.0139***	-0.0057***				0.1076
		(3.92)	(2.72)		(0.03)	(4.82)	(-2.59)				
	k=48	0.0186***	0.0042***		-0.0006	0.0140***	-0.0034*				0.1042
		(4.87)	(3.86)		(-1.09)	(4.66)	(1.87)				
	k=60	0.0188***	0.0043***		-0.0011**	0.0140***	-0.0020				0.1048
		(5.23)	(5.05)		(-2.32)	(4.50)	(-1.51)				

Panel C: Asia

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0218***	0.0039**								0.0511
		(4.66)	(2.42)								
(2)	k=36	0.0243***		0.0044**	0.0039**	0.0015	-0.0097***	0.0053	-0.0058***	0.0112**	0.1892
		(4.07)		(2.08)	(2.09)	(0.39)	(-4.14)	(1.23)	(-3.02)	(2.50)	
	k=48	0.0219***		0.0036*	0.0019	0.0025	-0.0053**	0.0044	-0.0034*	0.0078	0.1843
		(3.80)		(1.78)	(1.01)	(0.63)	(-1.97)	(0.88)	(-1.89)	(1.52)	
	k=60	0.0209***		0.0029	0.0033*	0.0025	-0.0080***	0.0058	-0.0047***	0.0105**	0.1844
		(3.29)		(1.34)	(1.82)	(0.71)	(-3.31)	(1.33)	(-2.59)	(2.52)	
(3)	k=36	0.0215***	0.0035*		-0.0001	0.0054	-0.0056**				0.1894
		(3.83)	(1.76)		(-0.04)	(1.24)	(-2.36)				
	k=48	0.0188***	0.0026		-0.0012	0.0054	-0.0021				0.1852
		(3.61)	(1.42)		(-0.92)	(1.18)	(-0.72)				
	k=60	0.0183***	0.0021		0.0009	0.0049	-0.0055**				0.1849
		(3.25)	(1.08)		(0.66)	(1.14)	(-2.38)				

Table 3.5. Cross-Sectional Regressions for Regions of Country-Industry Indexes (cont.)

Panel D: South America

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0314***	0.0079**								0.0454
		(2.65)	(2.21)								
(2)	k=36	0.0342*		0.0093*	0.0122***	-0.0041	-0.0117**	0.0081	0.0005	0.0075	0.2349
		(1.94)		(1.85)	(2.86)	(-0.46)	(-2.44)	(1.20)	(0.16)	(1.02)	
	k=48	0.0370**		0.0113**	0.0072**	0.0014	-0.0068	0.0087	0.0004	0.0082	0.2291
		(2.18)		(2.38)	(1.99)	(0.16)	(-1.61)	(1.29)	(0.16)	(1.09)	
	k=60	0.0250*		0.0069**	0.0068*	0.0024	-0.0077*	0.0091	-0.0010	0.0101	0.2309
		(1.86)		(2.02)	(1.75)	(0.29)	(-1.94)	(1.32)	(-0.40)	(1.30)	
(3)	k=36	0.0326**	0.0090*		0.0033	0.0048	-0.0028				0.2344
		(1.99)	(1.86)		(1.44)	(0.77)	(-0.71)				
	k=48	0.0355**	0.0110**		-0.0035***	0.0122*	0.0036				0.2276
		(2.25)	(2.26)		(-2.78)	(1.88)	(1.32)				
	k=60	0.0343**	0.0106***		-0.0009	0.0105	-0.0009				0.2276
		(2.31)	(2.60)		(-0.72)	(1.47)	(-0.37)				

Panel E: MENA

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0162***	0.0023								0.0525
		(2.64)	(1.22)								
(2)	k=36	0.0163**		0.0025	0.0017	0.0080	-0.0145***	0.0098	-0.0128**	0.0226***	0.2531
		(2.05)		(1.20)	(0.82)	(1.06)	(-2.57)	(1.42)	(-2.39)	(2.76)	
	k=48	0.0197***		0.0040*	0.0017	0.0109*	-0.0058*	0.0126**	-0.0041	0.0167**	0.2548
		(2.70)		(1.95)	(1.02)	(1.78)	(-1.95)	(2.27)	(-1.39)	(2.37)	
	k=60	0.0098		0.0015	0.0028*	0.0136**	-0.0041	0.0164***	-0.0013	0.0177***	0.2571
		(1.02)		(0.60)	(1.79)	(2.25)	(-1.37)	(3.13)	(-0.49)	(2.91)	
(3)	k=36	0.0157**	0.0023		-0.0006	0.0101	-0.0123**				0.2545
		(2.08)	(1.11)		(-0.32)	(1.44)	(-2.37)				
	k=48	0.0185***	0.0037*		-0.0019	0.0141**	-0.0022				0.2560
		(2.63)	(1.76)		(-0.93)	(2.51)	(-0.65)				
	k=60	0.0076	0.0008		0.0021	0.0139**	-0.0038				0.2580
		(0.85)	(0.30)		(0.71)	(2.34)	(-1.27)				

Table 3.5. Cross-Sectional Regressions for Regions of Country-Industry Indexes (cont.)

Panel F: Japan											
		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0162***	0.0030*								0.1008
		(2.79)	(1.84)								
(2)	k=36	0.0169**		0.0032	0.0051**	0.0074	-0.0049	0.0125*	0.0001	0.0123	0.4074
		(2.22)		(1.44)	(2.50)	(1.07)	(-0.82)	(1.81)	(0.02)	(1.24)	
	k=48	0.0214***		0.0051**	0.0063***	0.0074	-0.0058	0.0137*	0.0005	0.0132	0.4087
		(2.96)		(2.52)	(2.88)	(1.06)	(-1.37)	(1.84)	(0.13)	(1.61)	
	k=60	0.0204**		0.0046**	0.0043**	0.0072	-0.0038	0.0115*	0.0005	0.0110	0.4179
		(2.55)		(2.05)	(2.28)	(1.12)	(-0.94)	(1.70)	(0.12)	(1.57)	
(3)	k=36	0.0172**	0.0033		0.0018	0.0106	-0.0016				0.4078
		(2.29)	(1.51)		(0.79)	(1.46)	(-0.30)				
	k=48	0.0219***	0.0053***		0.0011	0.0126*	-0.0005				0.4081
		(3.07)	(2.64)		(0.51)	(1.84)	(-0.14)				
	k=60	0.0199***	0.0045**		-0.0002	0.0116*	0.0007				0.4171
		(2.56)	(2.04)		(-0.10)	(1.91)	(0.17)				

Table 3.6. Cross-Sectional Regressions for Size Portfolios of Country-Industry Indexes

This table presents the averages of the slope coefficients from the cross-sectional regressions of Equations (3.14), (3.15), and (3.16), which regress previous month's country-industry index returns on *EP* and its components for different size quintiles. *MV1* (*MV5*) is the portfolio including the country-industry indexes with the lowest (highest) market capitalization values. Panels A to F present the results for each size portfolio, respectively. All variables are as explained before (*EP*, LEP_k, dE_k, *MOM*, REV_k, dE_k+*MOM*, dE_k+REV_k, *MOM*-REV_k). The Newey-West (1987) adjusted *t*-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Low *MV*1

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0179***	0.0011								0.0551
		(2.62)	(0.48)								
(2)	k=36	0.0258***		0.0045	0.0058*	0.0137***	-0.0121**	0.0195***	-0.0063**	0.0258***	0.2244
		(2.69)		(1.40)	(1.83)	(2.87)	(2.31)	(3.80)	(-2.05)	(3.83)	
	k=48	0.0175*		0.0012	0.0022	0.0164***	-0.0072**	0.0186***	-0.0051**	0.0237***	0.2205
		(1.92)		(0.39)	(1.07)	(3.38)	(-2.25)	(4.27)	(-2.40)	(4.64)	
	k=60	0.0158*		0.0014	0.0018	0.0119**	-0.0048*	0.0136***	-0.0030*	0.0166***	0.2140
		(1.81)		(0.54)	(0.78)	(2.29)	(-1.89)	(3.33)	(-1.68)	(3.97)	
(3)	k=36	0.0240*	0.0040		0.0015	0.0181***	-0.0079**				0.2239
		(1.78)	(1.40)		(0.75)	(4.03)	(-2.00)				
	k=48	0.0175**	0.0014		0.0008	0.0177***	-0.0059*				0.2210
		(2.09)	(0.46)		(0.40)	(4.31)	(-1.90)				
	k=60	0.0157*	0.0018		0.0006	0.0119**	-0.0032*				0.2151
		(1.79)	(0.76)		(0.23)	(2.11)	(-1.69)				

Table 3.6. Cross-Sectional Regressions for Size Portfolios of Country-Industry Indexes (cont.)

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
Panel B: *MV*2											
(1)		0.0175***	0.0021**								0.0352
		(4.37)	(2.20)								
(2)	k=36	0.0185***		0.0037***	0.0022**	0.0128***	-0.0059***	0.0150***	-0.0037**	0.0187***	0.1622
		(3.42)		(3.01)	(2.16)	(3.15)	(-3.27)	(3.44)	(-1.99)	(4.05)	
	k=48	0.0174***		0.0033**	0.0024***	0.0131***	-0.0057***	0.0155***	-0.0033**	0.0188***	0.1620
		(3.03)		(2.42)	(2.90)	(3.11)	(-3.85)	(3.48)	(-2.30)	(4.32)	
	k=60	0.0158***		0.0027**	0.0024***	0.0129***	-0.0075***	0.0153***	-0.0051***	0.0204***	0.1636
		(2.81)		(1.97)	(3.03)	(3.02)	(-4.60)	(3.58)	(-3.31)	(4.49)	
(3)	k=36	0.0168***	0.0033***		-0.0013	0.0163***	-0.0023				0.1624
		(3.22)	(2.73)		(-1.20)	(3.62)	(-1.53)				
	k=48	0.0157***	0.0029**		-0.0006	0.0161***	-0.0027*				0.1625
		(3.82)	(2.16)		(-0.58)	(3.63)	(-1.71)				
	k=60	0.0145***	0.0024*		-0.0001	0.0155***	-0.0048***				0.1640
		(2.70)	(1.77)		(-0.16)	(3.41)	(-3.05)				
Panel C: *MV*3											
		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0207***	0.0043***								0.0316
		(4.87)	(3.10)								
(2)	k=36	0.0236***		0.0057***	0.0033**	0.0069*	-0.0077***	0.0102**	-0.0044**	0.0146***	0.1614
		(4.92)		(3.99)	(2.21)	(1.80)	(-3.35)	(2.50)	(-1.99)	(3.49)	
	k=48	0.0234***		0.0057***	0.0043***	0.0073*	-0.0074***	0.0116***	-0.0031**	0.0147***	0.1603
		(4.68)		(3.45)	(3.12)	(1.93)	(-3.79)	(2.85)	(-1.98)	(3.71)	
	k=60	0.0235***		0.0057***	0.0046***	0.0060	-0.0075***	0.0105***	-0.0029*	0.0134***	0.1569
		(4.63)		(3.78)	(3.13)	(1.53)	(-3.58)	(2.61)	(-1.91)	(3.43)	
(3)	k=36	0.0211***	0.0051***		-0.0020**	0.0123***	-0.0022				0.1617
		(4.48)	(3.54)		(-2.36)	(3.12)	(-1.02)				
	k=48	0.0208***	0.0050***		-0.0009	0.0124***	-0.0021				0.1604
		(4.38)	(3.17)		(-0.96)	(3.12)	(-1.19)				
	k=60	0.0212***	0.0052***		-0.0007	0.0111***	-0.0021				0.1572
		(4.39)	(3.58)		(-0.85)	(2.72)	(-1.21)				

Table 3.6. Cross-Sectional Regressions for Size Portfolios of Country-Industry Indexes (cont.)

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
Panel D: *MV*4											
(1)		0.0079*	-0.0001								0.0316
		(1.94)	(-0.06)								
(2)	k=36	0.0108**		0.0022*	0.0014	0.0127***	-0.0016	0.0141***	-0.0002	0.0144***	0.1662
		(2.37)		(1.82)	(1.28)	(3.51)	(-0.80)	(3.72)	(-0.11)	(3.42)	
	k=48	0.0113***		0.0021*	0.0009	0.0128***	-0.0020	0.0137***	-0.0011	0.0148***	0.1677
		(2.78)		(1.92)	(0.72)	(3.54)	(-0.95)	(3.56)	(-0.58)	(3.58)	
	k=60	0.0099**		0.0017	0.0009	0.0128***	-0.0023	0.0137***	-0.0013	0.0151***	0.1656
		(2.21)		(1.43)	(0.82)	(3.63)	(-1.44)	(3.75)	(-0.84)	(4.01)	
(3)	k=36	0.0096**	0.0018		-0.0005	0.0147***	0.0004				0.1660
		(2.23)	(1.59)		(-0.54)	(4.00)	(0.20)				
	k=48	0.0101***	0.0017*		-0.0010	0.0146***	-0.00001				0.1677
		(2.69)	(1.72)		(-1.03)	(4.03)	(-0.004)				
	k=60	0.0088**	0.0014		-0.0006	0.0143***	-0.0007				0.1657
		(2.12)	(1.25)		(0.68)	(3.99)	(-0.43)				
Panel E: High *MV*5											
		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0143***	0.0025								0.0835
		(2.85)	(1.52)								
(2)	k=36	0.0124**		0.0022	0.0023*	0.0063	-0.0058**	0.0086**	-0.0035	0.0120***	0.2413
		(2.43)		(1.24)	(1.76)	(1.44)	(-2.13)	(2.02)	(-1.43)	(2.74)	
	k=48	0.0136**		0.0026	0.0023**	0.0063	-0.0052**	0.0087**	-0.0029	0.0116***	0.2442
		(2.47)		(1.44)	(2.04)	(1.50)	(-2.22)	(2.09)	(-1.47)	(2.67)	
	k=60	0.0131**		0.0022	0.0018	0.0064	-0.0049**	0.0082**	-0.0030*	0.0113**	0.2428
		(2.26)		(1.17)	(1.43)	(1.50)	(-2.47)	(1.98)	(-1.95)	(2.52)	
(3)	k=36	0.0119**	0.0021		0.0002	0.0084*	-0.0036				0.2417
		(2.54)	(1.27)		(0.12)	(1.81)	(-1.28)				
	k=48	0.0127***	0.0024		-0.0002	0.0089**	-0.0027				0.2446
		(2.58)	(1.46)		(-0.12)	(2.00)	(-1.17)				
	k=60	0.0126**	0.0022		-0.0003	0.0086*	-0.0027*				0.2436
		(2.45)	(1.27)		(-0.20)	(1.91)	(-1.66)				

Table 3.7. Cross-Sectional Regressions for Size Portfolios of Country Indexes

This table presents the averages of the slope coefficients from the cross-sectional regressions of Equations (3.14), (3.15), and (3.16), which regress previous month's country index returns on *EP* and its components for different size quintiles. *MV1* (*MV3*) is the portfolio including the country indexes with the lowest (highest) market capitalization values. Panels A to C present the results for each size portfolio, respectively. All variables are as explained before (EP, LEP_k, dE_k, MOM, REV_k, dE_k+MOM, dE_k+REV_k, MOM-REV_k). The Newey-West (1987) adjusted *t*-statistics are reported in the parentheses. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Low *MV*1

		α_0	EP	LEP_k	dE_k	MOM	REV_k	dE_k+MOM	dE_k+REV_k	MOM-REV_k	R^2
(1)		0.0254**	0.0047								0.1328
		(2.11)	(1.00)								
	k=36	0.0436**		0.0140**	0.0056	-0.0091	0.0034	-0.0035	0.0090	-0.0125	0.4402
		(2.13)		(2.07)	(1.21)	(-0.69)	(0.41)	(-0.33)	(1.43)	(-1.06)	
(2)	k=48	0.0491**		0.0152**	0.0035	-0.0084	-0.0031	-0.0049	0.0004	-0.0053	0.4333
		(2.30)		(2.25)	(0.72)	(-0.66)	(-0.51)	(-0.46)	(0.14)	(-0.50)	
	k=60	0.0688**		0.0224**	0.0104	-0.0252	-0.0107	-0.0148	-0.0003	-0.0145	0.4255
		(2.25)		(2.10)	(1.31)	(-1.61)	(-1.49)	(-1.37)	(-0.09)	(-1.14)	
	k=36	0.0330	0.0101		-0.0063*	0.0033	0.0118				0.4375
		(1.60)	(1.47)		(-1.71)	(0.29)	(1.55)				
(3)	k=48	0.0331	0.0097		-0.0091**	0.0033	0.0086				0.4352
		(1.55)	(1.44)		(-2.01)	(0.26)	(1.52)				
	k=60	0.0222	0.0062*		-0.0067*	0.0010	0.0058				0.4247
		(1.08)	(1.95)		(-1.72)	(0.10)	(1.18)				

Table 3.7. Cross-Sectional Regressions for Size Portfolios of Country Indexes (cont.)

Panel B: *MV*2

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0434***	0.0132**								0.1373
		(2.87)	(2.45)								
(2)	k=36	0.0523***		0.0175***	0.0105	-0.0025	-0.0050	0.0080	0.0055	0.0025	0.4635
		(4.73)		(4.64)	(1.42)	(-0.23)	(-0.84)	(0.76)	(0.91)	(0.21)	
	k=48	0.0642***		0.0214***	0.0108*	-0.0042	-0.0164***	0.0066	-0.0056	0.0122	0.4619
		(4.51)		(4.36)	(1.77)	(-0.49)	(-3.36)	(0.66)	(-1.39)	(1.31)	
	k=60	0.0483***		0.0165***	0.0125*	-0.0065	-0.0123*	0.0060	0.0002	0.0058	0.4614
		(3.69)		(3.93)	(1.81)	(-0.72)	(-1.85)	(0.57)	(0.04)	(0.55)	
(3)	k=36	0.0401***	0.0133***		-0.0044	0.0123	0.0106**				0.4604
		(4.11)	(4.11)		(-0.87)	(1.28)	(2.51)				
	k=48	0.0511***	0.0175***		-0.0094*	0.0162**	0.0048				0.4567
		(4.07)	(3.80)		(-1.94)	(1.97)	(1.15)				
	k=60	0.0292***	0.0102***		-0.0019	0.0054	0.0026				0.4545
		(2.89)	(2.88)		(-0.38)	(0.58)	(0.52)				

Panel C: High *MV*3

		α_0	*EP*	LEP_k	dE_k	*MOM*	REV_k	dE_k+*MOM*	dE_k+REV_k	*MOM*-REV_k	R^2
(1)		0.0175**	0.0041*								0.1567
		(2.38)	(1.71)								
(2)	k=36	0.0080		0.0004	0.0026	-0.0088	0.0006	-0.0062	0.0031	-0.0093	0.5333
		(0.71)		(0.10)	(0.43)	(-0.80)	(0.05)	(-0.61)	(0.29)	(-0.89)	
	k=48	0.0127		0.0037	0.0006	-0.0004	0.0036	0.0002	0.0042	-0.0040	0.5350
		(1.30)		(1.30)	(0.14)	(-0.04)	(0.68)	(0.02)	(1.06)	(-0.37)	
	k=60	0.0149		0.0020	0.0092*	-0.0063	-0.0124***	0.0029	-0.0033	0.0061	0.5509
		(1.59)		(0.65)	(2.16)	(-0.62)	(-2.92)	(0.29)	(-1.05)	(0.55)	
(3)	k=36	0.0081	0.0004		0.0023	-0.0082	0.0001				0.5335
		(0.80)	(0.13)		(0.41)	(-0.73)	(0.01)				
	k=48	0.0109	0.0033		-0.0026	0.0028	0.0069				0.5362
		(1.22)	(1.23)		(-0.75)	(0.28)	(1.52)				
	k=60	0.0150*	0.0021		0.0076*	-0.0070	-0.0104**				0.5518
		(1.68)	(0.71)		(1.65)	(-0.60)	(-2.25)				

CONCLUSION

The first and second chapters focused on the potential cross-sectional effects of the nineteen index attributes on the expected index returns from the perspective of an international investor. The local industry indexes with 19 industries specified for 37 countries and 51 countries for the first and second chapters, respectively, were considered as the international assets.

The first chapter focused on several return predictors, such as measures of volatility, skewness, momentum, profitability; size and value effects; and several stand-alone measures, such as investments and net share issuance. The set of volatility measures also included a novel measure of total volatility, return range, defined as the difference between the maximum and minimum daily returns over the past month. Both portfolio-level analyses and the index-level cross-sectional regressions were performed. Bivariate portfolio sorts were also performed based on size and the other eighteen index attributes and index-level, cross-sectional regressions across size quintiles to investigate whether the behavior of anomalies reflects a size anomaly. Lastly, the conditional relationship between the total volatility measures of *Range* and *SD* was examined by performing bivariate portfolio analyses on each other.

The second chapter reported the portfolio-level analyses and the index-level cross-sectional regressions, performed by dividing the total sample of the country-industry indexes into six regions, North America, Europe, Asia-Pacific, South America, MENA (Middle East and North Africa), and Japan, to examine variations in the significance of the nineteen index attributes across regions. The analysis in the first chapter assumed that the total sample is fully integrated with the global market. Hence, it performed the international versions of the asset-pricing models. In contrast the analysis in the second chapter took into account regional characteristics, which affect the degree of market segmentation/integration across regions. Hence, it performed regional versions of the asset-pricing models.

The third chapter examined whether decomposing *EP* into its components increases the estimates of expected returns for the sample of country-industry indexes as well as the 51 country indexes. The *EP* ratio was decomposed into four independent components, namely lagged *EP* value, change in earnings, momentum, and reversal, in line with the decomposition methodology of Fama and French (2008). The decomposition analyses were also performed for developed and emerging markets, across six regions, and for different size portfolios in order to assess the validity of the *EP* decomposition across sub-samples.

Based on the results of the first chapter, which showed a strong correlation between the return range and other volatility measures, and a strong predictive ability on index returns, return range can be used as a more practical measure of total volatility than the widely used total volatility measure of standard deviation. Moreover, the results indicated that the volatility measures of return range, standard deviation, and idiosyncratic volatility in small-cap indexes, and maximum and minimum return anomalies in any size of indexes have strongly significant effects. In addition, there are skewness effects, especially in small-cap indexes, a momentum effect in both small-cap and medium-cap indexes that depended on the measurement approach, a profitability effect measured as return on equity and earnings surprise in small-cap and large-cap indexes, respectively, and a value effect in all size segments that depended on the definition.

The regional analyses presented in the second chapter indicate that there are significant cross-sectional relations between all volatility measures as well as the return range and the returns on the country-industry indexes from Europe, Asia-Pacific, South America, and Japan. On the other hand, in North America and MENA, only maximum and minimum return anomalies survive among all volatility measures. These results imply that the maximum and minimum return anomalies have persistently strong effects on index returns regardless of the region. Moreover, the size and value anomalies significantly affect returns on the country-industry indexes from North America, Europe, Asia-Pacific, South America, and MENA whereas in Japan, only the size effect is significant. The momentum effect also has significant explanatory power in North America, Europe, and MENA while the profitability effect provides abnormal returns for Europe and Asia-Pacific depending on its definition. The skewness effect, whether measured as total or idiosyncratic skewness, only has a significant effect for the European country-industry indexes. Lastly, a clear majority of the results of the portfolio analyses are supported by the results of the Fama-MacBeth regressions.

The analysis reported in the third dissertation chapter showed that the *EP* ratio significantly affects returns on both country-industry and country indexes in most cases, which means that high *EP* ratio indexes outperform low *EP* ratio indexes. Moreover, the *EP* components reveals hidden information in the *EP* ratio that can be used to enhance estimates of future returns for both country-industry and country indexes. In addition, the validity of the *EP* decomposition is robust for all regions of country-industry indexes except South America. The results for *EP* decomposition vary depending on the time horizons used for the lagged value of *EP*. Lastly, the decomposition analyses for the size-based portfolios of the country-industry and country indexes show that the *EP* components of provide additional information to the *EP* ratio alone for small-cap indexes.

The findings reported in this dissertation have several valuable implications for international investors aiming to diversify their portfolio across industry indexes and/or regional country-industry indexes. Firstly, determining the return predictors of the international index returns sheds light on the construction of trading strategies for international investors. Secondly, the size of the indexes has an important effect on the predictive ability of index attributes since the significance of these variables varies across different size segments, although it is mainly stronger for small-cap indexes. Thirdly, the significance of the anomalies also varies across regions because of differences in stock market conditions, market regulations, and economic activities. In other words, some anomalies may merely reflect global and/or local factors, which makes them region specific and/or global depending on market segmentation/integration. As a result, there are volatility, momentum, and value anomalies that provide arbitrage opportunities waiting to be exploited for small-cap indexes or different regions of country-industry indexes. Furthermore, the results of the *EP* ratio decomposition imply that decomposition matters not only for the US market, as shown previously in the literature, but also for international indexes. In addition, the varied results of *EP* decomposition across sub-samples of developed and emerging markets, size portfolios, regions, and different time horizons provide useful information for international investors.

REFERENCES

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance, 61*(1), 259–299.

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: international and further US evidence. *Journal of Financial Economics*, *91*(1), 1–23.

Angelidis, T., & Tessaromatis, N. (2014, forthcoming). Global style portfolios based on country indices. *Bankers, Markets & Investors*, Retrieved from: http://mpra.ub.uni-muenchen.de/53094.

Angelidis, T., & Tessaromatis, N. (2017). Global equity country allocation: An application of factor investing. *Financial Analysts Journal, 73*(4), 55-73.

Arditti, F. D. (1967). Risk and the required return on equity. *The Journal of Finance*, *22*(1), 19-36.

Arditti, F. D. (1971). Another look at mutual fund performance. *Journal of Financial and Quantitative Analysis*, *6*(03), 909-912.

Asness, C. S., Liew, J. M., & Stevens, R. L. (1997). Parallels between the cross-sectional predictability of stock and country returns. *The Journal of Portfolio Management*, *23*(3), 79-87.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, *68*(3), 929-985.

Baca, S. P., Garbe, B. L., & Weiss, R. A. (2000). The rise of sector effects in major equity markets. *Financial Analysts Journal, 56*(5), 34-40.

Bali, T., Brown, S., Murray, S., & Tang, Y. (2017). A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis, 52*(6), 2369-2397.

Bali, T. G., & Cakici, N. (2010). World market risk, country-specific risk and expected returns in international stock markets. *Journal of Banking & Finance, 34*(6), 1152-1165.

Bali, G. T., Cakici, N., & Fabozzi, F. J. (2013). Book-to-market and the cross-section of expected returns in international stock markets. *Journal of Portfolio Management, 39*(2), 101-115.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427-446.

Bali, T. G., Engle, R. F., & Murray, S. (2016). *Empirical asset pricing: The cross-section of stock returns*. John Wiley & Sons, Inc.

Balvers, R., & Wu, Y. (2006). Momentum and mean reversion across national equity markets. *Journal of Empirical Finance*, *13*(1), 24-48.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, *32*(3), 663-682.

Basu, S. (1983). The relationship between earnings yield, market value, and return for NYSE common stocks: Further Evidence. *Journal of Financial Economics*, *12*(1), 129–156.

Bekaert, G., & Harvey, C. R. (1995). Time-varying world market integration. *The Journal of Finance, 50*(2), 403-444.

Bekaert, G., & Mehl, A. (2017). On the global financial market integration ‘swoosh’ and the trilemma. Columbia Business School Research Paper No. 17-17. Retrieved May 20, 2017, from SSRN: https://ssrn.com/abstract=2904272

Bekaert, G., Harvey, C. R., & Lumsdaine, R. L. (2002). Dating the integration of world equity markets. *Journal of Financial Economics, 65*(2), 203-247.

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S. (2011). What segments equity markets?. *The Review of Financial Studies*, *24*(12), 3841-3890.

Bekaert, G., Hodrick, R.J., & Zhang, X. (2009). International stock return comovements. *Journal of Finance*, *64*(6), 2591-2626.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance, 43*(2), 507-528.

Bhojraj, S., & Swaminathan, B. (2006). Macromomentum: returns predictability in international equity indices. *The Journal of Business, 79*(1), 429-451.

Blackburn, D. W., & Cakici, N. (2019). Book-to-market decomposition, net share issuance, and the cross section of global stock returns. *Journal of Risk and Financial Management*, *12*(2), 90.

Blume, M. E., & Friend, I. (1973). A new look at the capital asset pricing model. The *Journal of Finance*, *28*(1), 19-33.

Bodie, Z., Kane, A., and Marcus, A. J. (2010). *Essentials of investments* (8th ed.). Boston: McGraw-Hill Irwin.

Boudoukh, J., Richardson, M., & Whitelaw, R. F. (1994). Industry returns and the Fisher effect. *The Journal of Finance, 49*(5), 1595-1615.

Boyer, B., Mitton, T., & Vorkink, K. (2010). Expected idiosyncratic skewness. *Review of Financial Studies*, *23*(1), 169-202.

Cakici, N., Chatterjee, S., & Topyan, K. (2015). Decomposition of book-to-market and the cross-section of returns for Chinese shares. *Pacific-Basin Finance Journal*, *34*, 102-120.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*(1), 57-82.

Carrieri, F., Errunza, V., & Hogan, K. (2007). Characterizing world market integration through time. *Journal of Financial and Quantitative Analysis, 42*(4), 915-940.

Chan, K., Hameed, A., & Tong, W. (2000). Profitability of momentum strategies in the international equity markets. *The Journal of Financial and Quantitative Analysis*, *35*(2), 153-172.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1995). Evaluating the performance of value versus glamour stocks The impact of selection bias. *Journal of Financial Economics*, *38*(3), 269-296.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *Journal of Finance, 51*(5), 1681-1713.

Chan, L. K. C., & Lakonishok, J. (2004). Value and growth investing: Review and update. *Financial Analysts Journal, 60*(1), 71-86.

Conine Jr., T. E., & Tamarkin, M. J. (1981). On diversification given asymmetry in returns. *The Journal of Finance*, *36*(5), 1143-1155.

De Jong, F., & De Roon, F. A. (2005). Time-varying market integration and expected returns in emerging markets. *Journal of Financial Economics, 78*(3), 583-613.

DeBondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance, 40*(3), 793-805.

Desrosiers, S., L'Her, J. F., & Plante, J. F. (2004). Style management in equity country allocation. *Financial Analysts Journal*, *60*(6), 40-54.

Errunza, V., & Losq, E. (1985). International asset pricing under mild segmentation: Theory and test. *The Journal of Finance, 40*(1), 105-124.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, *82*(3), 491–518.

Fama, E. F., & French, K. R. (2008). Average returns, B/M, and share issues. *The Journal of Finance*, *63*(6), 2971-2995.

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, *63*(4), 1653-1678.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457-472.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.

Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), 441-463.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, *81*(3), 607-636.

Ferreira, M. A., & Ferreira, M. A. (2006). The importance of industry and country effects in the EMU equity markets. *European Financial Management*, *12*(3), 341-373.

Foerster, S. R., & Karolyi, G. A. (1999). The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. *The Journal of Finance*, *54*(3), 981-1013.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1-25.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*(1), 24-37.

Fu, X., Arisoy, Y. E., Shackleton, M. B., & Umutlu, M. (2016). Option-implied volatility measures and stock return predictability. *The Journal of Derivatives*, *24*(1), 58-78.

Goetzmann, W. N., Li, L., & Rouwenhorst, G. (2005). Long-term global market correlations. *The Journal of Business*, *78*(1), 1-38.

Guo, H., Kassa, H., & Ferguson, M. F. (2014). On the relation between EGARCH idiosyncratic volatility and expected stock returns. *Journal of Financial and Quantitative Analysis*, 271-296.

Haugen, R. A., & Baker, H. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics*, *41*(3), 401-439.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance, 55*(3), 1263-1295.

Hou, K., Karolyi, G. A., & Kho, B. C. (2011). What factors drive global stock returns?. *The Review of Financial Studies*, *24*(8), 2527-2574.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, *28*(3), 650-705.

Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2010). Return reversals, idiosyncratic risk, and expected returns. *The Review of Financial Studies*, *23*(1), 147-168.

Hueng, C. J. (2014). Are global systematic risk and country-specific idiosyncratic risk priced in the integrated world markets? *International Review of Economics and Finance*, *33*, 28-38.

Jaffe, J., Keim, D. B., & Westerfield, R. (1989). Earnings yields, market values, and stock returns. *The Journal of Finance*, *44*(1), 135-148.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance*, *45*(3), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65–91.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389-416.

Keppler, M., & Encinosa, P. (2011). The small-country effect revisited. *Journal of Investment*, *20*(4), 99–103.

Keppler, A. M., & Traub, H. D. (1993). The small-country effect: Small markets beat large markets. *The Journal of Investing*, *2*(3), 17-24.

Kim, D. (2012). Value premium across countries. *The Journal of Portfolio Management, 38*(4), 75-86.

La Porta, R. (1996). Expectations and the cross-section of stock returns. *The Journal of Finance, 51*(5), 1715-1742.

Lakonishok, J., & Shapiro, A. (1986). Systematic risk, total risk, and size as determinants stock market returns. *Journal of Banking & Finance*, *10*(1), 115-132.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), 1541-1578.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), 1-28.

Levy, R. A. (1967). Relative strength as a criterion for investment selection. *The Journal of Finance*, *22*(4), 595-610.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, *20*(4), 587-615.

Litzenberger, R. H., & Ramaswamy, K. (1979). The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of Financial Economics*, *7*(2), 163-195.

Liu, M., Liu, Q., & Ma, T. (2011). The 52-week high momentum strategy in international stock markets. *Journal of International Money and Finance, 30*(1), 180-204.

Macedo, R. (1995). Country-selection style. In: Lederman, J., Klein, R.A. (Eds.), *Equity style management: Evaluating and selecting investment styles*. Irwin Professional Publishing, Burr Ridge.

Malin, M., & Bornholt, G. (2013). Long-term return reversal: Evidence from international market indices. *Journal of International Financial Markets, Institutions and Money, 25*, 1-17.

Malkiel, B. G., & Xu, Y. (2004). Idiosyncratic risk and security returns. Retrieved from SSRN: http://dx.doi.org/10.2139/ssrn.255303.

Merton, R. C. (1987). A Simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483-510.

Mitton, T., & Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies*, *20*(4), 1255-1288.

Moerman, G. A. (2008). Diversification in Euro area stock markets: Country versus industry. *Journal of International Money and Finance, 27*(7), 1122-1134.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance, 54*(4), 1249-1290.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the Econometric Society*, 768-783.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703-708.

Phylaktis, K., & Xia, L. (2006). The changing roles of industry and country effects in the global equity markets. *The European Journal of Finance, 12*(8), 627-648.

Reinganum, M. R. (1981). A new empirical perspective on the CAPM. *Journal of Financial and Quantitative Analysis,* 439-462.

Richards, A. J. (1997). Winner-loser reversals in national stock market indices: Can they be explained? *The Journal of Finance, 52*(5), 2129-2144.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management, 11*(3), 9-16.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*(3), 341-360.

Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, *5*(3), 309-327.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425-442.

Simkowitz, M. A., & Beedles, W. L. (1978). Diversification in a three-moment world. *Journal of Financial and Quantitative Analysis*, *13*(5), 927-941.

Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, *71*(3), 289-315.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288-302.

Umutlu, M. (2015). Idiosyncratic volatility and expected returns at the global level. *Financial Analysts Journal, 71*(6), 58-71.

Umutlu, M. (2019). Does idiosyncratic volatility matter at the global level?. *The North American Journal of Economics and Finance, 47*, 252-268.

Umutlu, M., Akdeniz, L., & Altay-Salih, A. (2010a). The degree of financial liberalization and aggregated stock-return volatility in emerging markets. *Journal of Banking and Finance, 34*(3), 509-521.

Umutlu, M., Altay-Salih, A., & Akdeniz, L. (2010b). Does ADR listing affect the dynamics of volatility in emerging markets?. *Finance a Uver-Czech Journal of Economics and Finance, 60*(2), 122-137.

Umutlu, M., & Bengitöz, B. (2020). The cross-section of industry equity returns and global tactical asset allocation across regions and industries. *International Review of Financial Analysis, 72*, 101574.

Wang, C-J., Lee, C-H., & Huang, B-N. (2003). An analysis of industry and country effects in global stock returns: Evidence from Asian countries and the US. *The Quarterly Review of Economics and Finance*, *43*(3), 560-577.

Weiss, R. A. (1998). Global sector rotation: New look at an old idea. *Financial Analysts Journal*, *54*(3), 6-8.

Zaremba, A. (2015). Country selection strategies based on value, size, and momentum. *Investment Analysts Journal, 44*(3), 171-198.

Zaremba, A. (2016a). Is there a low-risk anomaly across countries? *Eurasian Economic Review*, *69*(1), 45-65.

Zaremba, A. (2016b). Investor sentiment, limits to arbitrage, and the performance of cross-country stock market anomalies. *Journal of Behavioral and Experimental Finance, 9,* 136-163.

Zaremba, A. (2016c). Risk-based explanation for the country-level size and value effects. *Finance Research Letters, 18,* 226-233.

Zaremba, A. (2020). Small-minus-big predicts betting-against-beta: Implications for international equity allocation and market timing. *Investment Analysts Journal*, *49*(4), 322-341.

Zaremba, A., & Umutlu, M. (2018). Size matters everywhere: Decomposing the small country and small industry premia. *North American Journal Economics and Finance, 48,* 1-18.

Zaremba, A., Umutlu, M., & Karathanasopoulos, A. (2019). Alpha momentum and alpha reversal in country and industry equity indexes. *Journal of Empirical Finance, 53,* 144-161.