WILMA DE GROOT

Assessing Asset Pricing Anomalies

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Het beoordelen van prijsanomalieën in beleggingsobjecten

Thesis

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Preface

I never really had the ambition to write a PhD thesis. Applying academic insights in practice, by developing investment strategies, always seemed more appealing than carrying out academic research. In addition, cooperating in a team and realizing joint objectives seemed more attractive than the lonely job of a PhD student. Although I still feel that way, the experience and knowledge I gained by writing this dissertation is extremely valuable. I am glad I took this opportunity.

After having written several academic papers as a spin-off of research I conducted at Robeco, colleagues suggested to push further and to write a PhD thesis. This was indeed the logical next step and I am grateful for all their support I got along the way.

I would like to thank my promotor Marno Verbeek and co-promotor Jules van Binsbergen for their trust and support. Their feedback and suggestions definitely brought my research to a higher level.

Moreover, thanks go to my co-authors of the chapters in this thesis. Joop Huij, Juan Pang, Laurens Swinkels and Weili Zhou, this dissertation has its current form owing to our cooperation.

Special thanks go to Peter Ferket and Leni Boeren. Peter, I am very happy for your guidance and encouragement to write this thesis, from the beginning until the very end. Leni, I appreciate your close involvement and advice on how to most efficiently combine my PhD project with various other ambitions.

I want to thank all my friends for their interest in my research, but especially for having a lot of fun. And for letting me open my laptop at social occasions. Thank you Froukje and Weili for being my 'paranimfen'.

Obviously, I am very grateful to the people closest to me, my parents, my sister José, and my (in-law) family for their help, love and support.

Combining a PhD track with a full-time job, giving birth to and raising kids is not the most ideal combination. I could not have done this without you, Stefan. I cannot thank you enough for the time I needed during weekends and evenings to work on this dissertation, but also for the valuable feedback content wise. Thanks for being my life partner. And sweet kisses for our big little boys, Luc, Cas and Sef for all your love and hugs I received along the way.

Wilma de Groot

Contents

1. Introduction

One of the most important challenges in the field of asset pricing is to understand anomalies: empirical patterns in asset returns that cannot be explained by standard asset pricing models such as the Capital Asset Pricing Model (CAPM). An example of a well-known asset pricing anomaly is the value anomaly. A range of academic studies have shown that value stocks with high book-to-price ratios yield a return premium, i.e.: higher returns than predicted by the CAPM. Many more asset pricing anomalies exist, some of which appear to be more persistent than others. In this dissertation, I focus on five well-known anomalies: value, momentum, size, low-risk and short-term reversal.

So, why do asset pricing anomalies exist? Currently, there is no consensus in the academic literature on the underlying causes of these anomalies. However, the explanations that have been given in different studies can be grouped into four categories: 1) the anomaly is a result of data mining; 2) the anomaly disappears when trading costs are taken into account; 3) the return premium associated with the anomaly is a compensation for a particular form of risk or 4) the anomaly has a behavioral explanation, meaning that behavior of market participants systematically influences asset prices and thereby causes market inefficiencies.

Understanding asset pricing anomalies is of the utmost importance for investors. It allows them to make better informed investment decisions, and thereby achieve higher return premiums. Let us take as an example the value anomaly. Investors can create an investment strategy to exploit this anomaly by creating a market capitalization weighted portfolio of the 20 percent stocks with the highest book-to-price ratios and repeat this every month. How does understanding of this anomaly actually help to achieve higher return premiums? Let us walk through the four categories of explanations and start with the data mining explanation. The robustness of the value effect can be determined by analyzing the anomaly on different data sets than the one where the anomaly was discovered, such as other regional samples or different time periods. If the anomaly is not robust, this means that exploiting it will likely result in disappointing out-of-sample results. Vice versa, the more evidence on the existence of the value anomaly, the higher the probability that investors are able to capture the premium.

Second, although an anomaly might lead to theoretically strong premiums, if these are eaten up by trading costs, an investor ends up with lower return premiums than expected. If the trading costs are too high to capture the value premium, investors need to think about smarter ways of implementing the investment strategy, for example by trading slower. A careful trade-off between gross returns on the one hand and trading costs on the other hand can lead to higher return premiums net of trading costs.

Third, if it is common knowledge that the return premium of the value anomaly is in fact a compensation for risk, investors can make an appropriate trade-off between risk and return. However, if the value anomaly does not appear to be a compensation for risk, one does not need to take that risk on board to capture the value premium. Investors can then create advanced investment strategies to capture the return premium with lower risk.

Finally, if the explanation of the value anomaly is more behavioral, the investor can make a judgement whether this behavior will continue to exist in the future. If the behavior disappears, the investor should not be surprised that the anomaly will also cease to exist. But if the behavior is structural, for example, because of the set-up of financial markets, investors can be more confident to capture the return premium going forward.

The motivation of this thesis is to gain more and better insight in possible explanations for well-known asset pricing anomalies. Each of the next four chapters of this thesis focuses on one of the four categories of explanations for asset pricing anomalies.

Chapter 2 analyzes whether well-known asset pricing anomalies, i.e. value, momentum, size and low-risk factors, are also present in the new emerging equity markets, the so-called frontier emerging markets.[1] We investigate whether these asset pricing anomalies that have been documented in developed countries also exist in these markets, where they have not been analyzed before. The sample serves as a clear out-of-sample test, as it is a unique dataset of more than 1,400 stocks over the period 1997 to 2008 and covers 24 of the most liquid frontier emerging markets. We document the presence of economically and statistically significant value and momentum effects, and a local size effect and can therefore conclude that data mining as an explanation for these effects is unlikely. Our results indicate that the value and momentum effects still exist when incorporating conservative assumptions of transaction costs. Additionally, we show that value, momentum, and local size returns in frontier markets cannot be explained by these effects in global international markets. We therefore indicate that global risk factors are less plausible to account for the effects and conclude that local risk factors or investors' behavior are more likely to explain the investigated anomalies.

Chapter 3 focuses on trading costs as a possible explanation for the short-term reversal anomaly.[2] Although trading costs are relevant for every asset pricing anomaly when

[1] This chapter is published as De Groot, W., Pang, J., and Swinkels, L., 2012, The cross-section of stock returns in frontier emerging markets, *Journal of Empirical Finance*, 19, 796-818.
[2] This chapter is published as De Groot, W., Huij, J. and Zhou, W., 2012, Another look at trading costs and short-term reversal profits, *Journal of Banking and Finance*, 36, 371-382.

it is being exploited by investors, the short-term reversal effect is the most interesting anomaly on which to analyze the effect. Gross returns are very high for this strategy, but so are turnover and therefore trading costs. The trade-off between gross-returns and trading costs for this strategy is therefore extremely delicate. Several studies report that the return premium associated with short-term reversal investment strategies diminishes once trading costs are taken into account. We show that the impact of trading costs on the strategies' profitability can largely be attributed to excessive trading in small-cap stocks. Limiting the stock universe to large-cap stocks significantly reduces trading costs. Applying a more sophisticated portfolio construction algorithm to lower turnover reduces trading costs even further. Our finding that reversal strategies generate 30–50 basis points per week net of trading costs poses a serious challenge to standard rational asset pricing models. Our findings also have important implications for the understanding and practical implementation of reversal strategies.

Chapter 4 examines risk as an explanation for the value and size effects.[3] Following the work of Fama and French (1992, 1993), a large stream of literature has been developed on the small-cap and value anomalies and numerous attempts have been made to better understand the economic origins of these anomalies. In particular, several papers attribute the small-cap and value anomalies to a common risk factor and contend that the premiums are compensation for investors bearing distress risk. We revisit the question whether the Fama-French factors are a manifestation of distress risk premiums. To this end, we develop new tests specifically aimed at dissecting the Fama-French factor returns from a distress risk premium. While we find that value and small-cap exposures are typically associated with distress risk, our results also indicate that distress risk is not priced and that the small-cap and value premiums are priced beyond distress risk. Moreover, the distress risk exposures of common small-cap and value factors do not have explanatory power in asset pricing tests. Our results have important implications for investors engaging in small-cap and value strategies, as by avoiding distress risk, they can capture the value and small-cap premiums with much lower risk.

Chapter 5 examines a behavioral explanation for the low-risk anomaly.[4] Due to the large shift of assets from individual investors to fund managers over the past decades, the impact of these managers' behavior on asset prices has grown. A large stream of literature has been developed on an important behavioral characteristic of these intermediaries,

[3] This chapter is based on De Groot, W., and Huij, J., 2017, Are the Fama-French factors really compensation for distress risk, resubmitted to the *Journal of International Money and Finance*.
[4] This chapter is based on De Groot, W., 2017, The low-risk anomaly and mutual fund tournaments, *working paper*.

namely tournament behavior. In this chapter we examine the relationship between tournament behavior of mutual fund managers and the low-risk anomaly. Based on a general equilibrium model we show that tournament behavior causes the returns of low-risk (high-risk) assets to be larger (smaller) than expected according to the Capital Asset Pricing Model. Using mutual fund data and pricing data of individual assets from twelve different asset categories, we find a positive and significant relation between tournament behavior and the low-risk premium. The results indicate that the low-risk effect is not only more prominent in a period following stronger tournament behavior, but is also larger in asset categories where more tournament behavior is observed. As there is no reason to assume that tournament behavior among mutual fund managers is likely to disappear anytime soon, investors can be more confident to capture the low-risk premium going forward.

2. The cross-section of stock returns in frontier emerging markets[5]

In this chapter we investigate the cross-section of stock returns in the new emerging equity markets, the so-called frontier emerging markets. Our unique survivorship-bias free data set consists of more than 1,400 stocks over the period 1997 to 2008 and covers 24 of the most liquid frontier emerging markets. The major benefit of using individual stock characteristics is that it allows us to investigate whether return factors that have been documented in developed countries also exist in these markets. We document the presence of economically and statistically significant value and momentum effects, and a local size effect. Our results indicate that the value and momentum effects still exist when incorporating conservative assumptions of transaction costs. Additionally, we show that value, momentum, and local size returns in frontier markets cannot be explained by global risk factors.

2.1. Introduction

Traditional emerging markets have developed rapidly over the past decades, both economically and financially. A group of countries less developed than emerging markets with established stock exchanges has appeared on the radar screen of global investors. These new emerging markets as a group are also known as frontier emerging markets, or in short, frontier markets. These countries vary greatly in their economic development. The GDP per capita in 2008 of Bangladesh, for example, is just $497 while that of Slovenia is $27,019.[6] The market capitalization of stocks in frontier emerging markets in October 2008 is $113.6 billion.[7] Although still smaller than traditional emerging and developed stock markets, these markets are becoming more important, as evidenced for example by recent listings of new mutual funds and exchange-traded funds on frontier markets.[8] In addition, for academics,

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[5] This chapter is published as De Groot, W., Pang, J., and Swinkels, L., 2012, The cross-section of stock returns in frontier emerging markets, *Journal of Empirical Finance*, 19, 796-818.

[6] Data source: World Bank Development Indicators, available online at http://data.worldbank.org. For comparison the GDP per capita of some other countries: Brazil $8,205, Russia $11,832, India $1,019, China $3,267, Afghanistan $366, Portugal $22,923, and the United States $46,350.

[7] This is the market capitalisation of the constituents of the Standard & Poor's Frontier Broad Market Index. Actual market capitalisation is higher because of exchange listed stocks that are not in this index and adjustments made to exclude the market capitalization part of the company that is inaccessible to (foreign) investors.

[8] For example, the Harding Loevner Frontier Emerging Markets Institutional (ticker: HLFMX) fund was launched on 27 May 2008 (total assets 5/31/2012: $68 mln), the Morgan Stanley Frontier Emerging Markets (ticker: FFD) fund was launched on 22 August 2008 (total assets 3/31/2012: $78

frontier emerging markets are an untapped data source that provides excellent out-of-sample research opportunities.

Investors who are interested in improving the risk-return trade-off of their portfolios could expand their investment opportunity set by including frontier equity markets. Goetzmann, Li, and Rouwenhorst (2005) indicate that investors should be willing to keep expanding their investment horizon to new equity markets to get a better diversified portfolio. Speidell and Krohne (2007) also mention diversification benefits as a key motivation for investors to include frontier markets in their investment portfolios. Berger, Pukthuanthong, and Yang (2011) investigate whether frontier equity markets are integrated with developed equity markets and conclude that this is not the case. These studies have in common that they consider frontier markets as a group or consider them at the country level. However, little is known about the risk, return, and diversification characteristics of return factors based on individual stock data in frontier markets.[9] Our unique survivorship-bias free data set on individual stock characteristics in frontier markets allows us to construct portfolios based on other characteristics than the country of stock exchange listing. Hence, we are able to investigate the existence of value, momentum, size, and low-risk effects in these markets over the period 1997 to 2008 and gauge how much stronger these effects are when employed at the stock rather than the country level. Moreover, our data enables us to investigate whether investment strategies based on these cross-sectional stock attributes are correlated between developed, emerging, and frontier markets. Our research aims to fill these gaps in the literature.

This study contributes to the literature on at least three dimensions. First, our results provide out-of-sample evidence for the existence of value, momentum, and local size effects. Sorting stocks in frontier markets on value characteristics, such as book-to-price ratios, momentum characteristics, such as past 6-month returns, or market capitalization per country yield statistically significant positive excess returns for the top quintile portfolios versus the index of 5% to 15% per annum. Our study extends the results by Fama and French (1998) and Rouwenhorst (1999) for international evidence on the value effect. Our results also reinforce the international evidence of the momentum effect reported by Griffin, Ji, and Martin (2003) and Rouwenhorst (1998, 1999). Our results are further empirical evidence

mln), the Templeton Frontier Markets (ticker: TFMAX) fund was launched on 14 October 2008 (total assets 4/30/2011: $383 mln), the Forward Frontier Markets (ticker: FRNMX) fund was launched on 31 December 2008 (total assets 5/31/2012: $70 mln) and the Guggenheim Frontier Markets (ticker: FRN) exchange-traded fund was launched on 12 June 2008 (total assets 4/30/2012: $137mln). Sources: Morningstar and Yahoo Finance.

[9] A notable exception is Girard and Sanha (2008), who use individual stock data of frontier markets to assess the importance of political risk in frontier market investments.

that value and momentum are present everywhere, as suggested by Asness, Moskowitz, and Pedersen (2013). The presence of a local size effect confirms evidence in Europe by Heston, Rouwenhorst, and Wessels (1999) and emerging markets by Rouwenhorst (1999). Our results are important, as frontier markets are least integrated with developed and emerging equity markets, yet, the cross-section of stock returns seems to produce excess returns on exactly the same factors.

Second, we are the first to investigate the profitability of value and momentum effects in frontier markets in detail when faced with real life market imperfections. We incorporate transaction costs estimates of 2.5% per single-trip transaction from Marshall, Nguyen, and Visaltanochoti (2013) covering bid-ask spreads, market impact and commissions. We deem this to be a conservative estimate as we consider the largest half of our sample and apply a one-month lag between ranking and portfolio formation to account for possible opportunity costs. Our empirical findings indicate that transaction costs have a large impact on the profitability of value and momentum strategies. However, we still observe economically and statistically significant returns of approximately 6.6% to 7.7% per annum after incorporating transactions costs for value strategies and net returns of 4.6% to 7.2% for momentum strategies. These findings seem to be inconsistent with market efficiency.

Third, we analyze whether exposure to global risk factors can explain the existence of the factor anomalies and whether the factors are prone to extreme downside risk. We document that the value, momentum, and local size effects in frontier markets cannot be explained by value, momentum, and local size effects in developed and emerging markets. This indicates that the excess returns are not caused by exposures to global risk factors and implies that our findings are independent of the existence of the effects in other markets. In addition we show that the downside risk of value, momentum and local size portfolios in frontier markets is lower than can be expected based on the assumptions of normality. Hence, we deem it unlikely that downside risk can explain the empirical results we document.

This chapter is organized as follows. We start in Section 2.2 by describing the data and methodology used in our analyses. We investigate the value, momentum, size and low-risk effect in more detail in Section 2.3. In Section 2.4 we incorporate transactions costs in order to determine whether the cross-sectional return patterns still exist when faced with real life market imperfections. In Section 2.5 we investigate whether value, momentum, and local size effects in frontier markets can be explained by global risk factors. Finally, Section 2.6 concludes.

2.2. Data and methodology

Our research on individual stocks in frontier emerging markets makes use of a unique data set with high quality data from different sources. In this section we describe our data collection procedure.

All stocks are index constituents of the Standard & Poor's Frontier Broad Market Index (S&P Frontier BMI). The sample period runs from the inception of the index in January 1997 to November 2008, meaning our sample contains almost 12 years of data. The firm characteristics that we use to investigate the value effect are book-to-market ratios, earnings-to-price ratios, and dividend yields. We use past local stock returns ranging from 6 to 36 months to investigate momentum[10] and low-volatility strategies and past 36 months dollar stock returns to construct the beta strategy. We use market capitalizations to investigate the size effect.

2.2.1. Sample selection

Standard and Poor's (S&P) selects the S&P Frontier BMI constituents according to their country as well as according to company selection criteria. To select countries, they analyze potential frontier markets for investor interest and accessibility. A market's turnover, number of listings and whether it has attracted a minimum amount of foreign investor interest are considered. S&P also considers a market's development prospects and, in particular, whether a market is likely to develop in breadth, depth and infrastructure. These requirements ensure that many small and inaccessible countries are not included in our data set.

In each country, S&P selects the publicly listed equities, including local listings and listings from Hong Kong, London and New York, based on market capitalization and lack of foreign investment restrictions. The aggregation of the market capitalization of selected stocks should exceed 80% of the total market capitalization of each country. S&P reduces the number of shares outstanding used in the index calculation to reflect any limits or restrictions on investments by foreign investors or entities. Hence, our sample contains only the larger and more investable part of frontier equity markets. Our sample does not suffer from survivorship bias, as the index constituents are known real-time. Each month,

[10] This is in line with Bhojraj and Swaminathan (2006), whose results suggest that using local returns for international momentum strategies leads to higher excess returns.

we include only those stocks in our sample that are index constituents at that moment in time.[11]

Table 2.1 shows the frontier market countries in our sample with, in column two, the region classification and, in columns three to seven, country inclusion information: dates of inclusion in index, country index weights and number of firms at the moment of inclusion and as of the last sample month of October 2008. The largest countries (in terms of index weight) in October 2008 are Kazakhstan, Lebanon and Slovenia. During the sample period, the number of countries increased from 14 to 24, and the number of firms increased from 204 to 290. The last two columns contain the turnover ratio of stocks in a particular country in the inclusion year in the index and in 2008. The turnover ratio is a measure of liquidity and defined as the total value of stock trades in a year divided by the average market capitalization of the entire stock market. This data is obtained at the country level from the World Bank online database.[12] The turnover rate for developed markets is typically between 50% and 150%. For emerging markets the turnover rate is generally between 25% and 75%. The turnover rate in frontier markets is on average close to 15%, which is substantially smaller than for developed markets. In 2008, the frontier countries with the largest turnover ratios are Bangladesh, Tunisia, and Vietnam.

2.2.2. Returns and market capitalizations

We calculate stock returns as monthly total returns in US dollars. Since S&P does not provide total return data for individual stocks in frontier markets, we use total monthly returns from Interactive Data Exshare as our first data source. If total return data is not available from Exshare, then we aggregate S&P monthly price returns and the cumulative daily dividend in that month divided by the price at the previous month-end to get monthly total returns. In case of extreme monthly return observations with large differences between the above two data sources, we check with alternative data sources, such as Bloomberg or the local stock exchange.[13] If one of the total returns still cannot be confirmed, we use the smallest available in absolute value to limit the potential influence of outliers.

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[11] Still, one could wonder whether the historical index has been constructed using future information. We verified with the IFC Emerging Stock Markets Factbook 1998 and the index construction methodology by S&P that no surviving countries were later added to the historical index. We also verified that no countries were excluded from the index during our sample period.

[12] Data retrieved from http://data.worldbank.org/indicator/CM.MKT.TRNR. Note that we cross-checked the data for 1997 with those available in the IFC Emerging Stock Markets Factbook 1998 and find that these are similar.

[13] We define monthly total returns larger than 100% and smaller than -60% as extreme returns.

TABLE 2.1. Summary statistics of frontier markets firms

The table gives for each country the *region* classification, the *inclusion date* in the S&P Frontier BMI, the (end of month) *index weights* at the inclusion date and in October 2008, the *number of firms* at the inclusion date and October 2008, the *average monthly return* and the *standard deviation* of the returns of the equally-weighted index of the sample firms over the period since the inclusion date until November 2008, both in local currency (LC) and US dollars (USD). The next four columns show the summary statistics median *firm size*, median *book-to-market ratio (B/M)*, median *earnings-to-price ratio (E/P)*, and median *dividend yield (D/P)* of the sample firms. Size is measured as the market capitalization of the firms in millions of US dollars. The medians are computed per month across firms, and the table reports the time series average of these monthly medians. The turnover ratio is a country average of the value of stock trades divided by the market capitalization in the inclusion year and 2008. In addition, the average of the statistics is displayed. The bottom rows show statistics for the equally-weighted (EW) and value-weighted (VW) index and the difference between the two. In the last row, the number between brackets is the t-value corresponding to the hypothesis that the average returns of the EW and VW index are the same.

		Inclusion	Index weights (%)		Number of firms		LC Return (%)		USD Return (%)		Median	Median	Median	Median	Turnover ratio	
Country	Region	date	Begin	Oct-08	Begin	Oct-08	Mean	Std.Dev.	Mean	Std.Dev.	size	B/M	E/P (%)	D/P (%)	Begin	2008
Bangladesh	Asia	Jan-97	19.1	4.7	46	25	0.5	7.6	0.2	7.8	17	0.8	8.8	3.3	12.6	137.3
Botswana	Africa	Jan-97	1.6	2.4	7	6	2.6	5.0	2.1	5.8	102	0.2	8.2	5.6	12.6	3.1
Bulgaria	Europe	Jan-97	0.03	0.9	12	11	1.4	8.8	1.4	11.2	19	1.6	9.3	0.2	-	10.8
Côte d'Ivoire	Africa	Jan-97	4.2	5.0	7	13	1.3	4.9	1.4	6.0	46	0.7	11.7	5.6	2.2	4.1
Croatia	Europe	Jan-98	9.1	5.4	8	15	1.6	9.0	1.7	9.3	87	1.5	9.9	0.9	2.8	7.4
Ecuador	America	Jan-97	8.7	3.2	11	6	1.7	5.2	0.4	7.0	86	0.9	10.6	4.4	8.7	3.6
Estonia	Europe	Jan-98	5.4	1.0	12	7	0.2	9.0	0.6	9.2	45	0.6	8.1	2.0	113.8	19.6
Ghana	Africa	Jan-97	8.0	1.4	7	10	3.2	6.7	1.9	7.4	30	0.4	17.7	3.5	3.7	5.2
Jamaica	America	Jan-97	11.3	3.5	22	15	2.2	8.4	1.6	8.3	45	0.9	12.8	3.4	3.7	3.6
Kazakhstan	Europe	Dec-07	17.9	13.8	13	13	-2.0	19.8	-2.0	19.7	600	0.5	10.1	-	20.9	9.5
Kenya	Africa	Jan-97	10.9	4.8	16	20	1.8	7.0	1.6	7.9	46	0.5	8.5	4.4	5.8	11.8
Latvia	Europe	Jan-98	1.3	0.2	11	9	0.1	8.9	0.2	9.2	7	2.8	10.0	0.3	23.6	1.8
Lebanon	Asia	Sep-99	8.4	11.4	5	5	1.3	7.8	1.3	7.8	331	1.0	2.7	0.9	4.2	6.9
Lithuania	Europe	Jan-97	2.2	0.9	31	15	0.6	6.9	0.9	7.7	23	1.1	9.5	0.7	18.0	7.1
Mauritius	Africa	Jan-97	6.6	3.9	13	9	1.0	4.3	0.7	4.8	45	0.9	11.2	4.8	8.1	8.9
Namibia	Africa	Sep-99	2.1	0.3	9	4	1.4	6.5	1.2	8.9	21	0.6	14.4	3.1	4.0	2.8
Panama	America	Dec-07	2.4	5.6	11	11	-2.7	6.7	-0.1	1.5	77	0.6	7.2	-	2.0	4.0
Romania	Europe	Jan-98	3.8	4.3	33	15	1.1	9.7	0.3	10.8	36	0.8	6.1	0.2	72.6	11.3
Slovakia	Europe	Nov-04	2.1	0.7	4	6	2.1	5.3	2.7	7.2	40	2.4	10.3	2.8	18.2	0.4
Slovenia	Europe	Jan-97	5.2	10.2	10	10	1.0	5.6	0.9	6.5	166	1.1	6.2	1.7	30.7	6.9
Trinidad & Tobago	America	Jan-97	7.8	6.5	11	6	1.3	4.3	1.3	4.4	237	0.3	6.5	2.3	5.9	2.6
Tunisia	Africa	Jan-97	14.4	3.5	11	17	0.6	4.0	0.4	4.4	57	0.7	8.0	4.2	7.9	25.5
Ukraine	Europe	Jan-98	4.2	2.3	17	18	3.9	17.9	3.1	18.3	70	2.3	12.4	0.0	4.4	3.7
Vietnam	Asia	Dec-06	9.4	4.0	18	24	-2.3	17.5	-2.4	17.9	107	0.1	2.7	0.0	22.4	44.8
Average	-	-	6.9	4.2	14	12	1.0	8.2	0.9	8.7	98	1.0	9.3	2.5	17.8	14.3
EW Index	-	Jan-97	-	100	-	290	1.4	4.0	0.8	4.2	-	-	-	-	-	-
VW Index	-	Jan-97	-	100	-	290	1.1	3.9	0.8	4.1	-	-	-	-	-	-
EW minus VW	-	-	-	-	-	-	0.3 (1.2)	-	0.1 (0.4)	-	-	-	-	-	-	-

To further gauge the quality of our data, we replicate the index returns for the individual countries in the S&P Frontier BMI in US dollars and local currency using total returns, S&P market capitalization, and index constituent identifiers in our individual stock database. The correlation between our replication and the index returns reported by S&P is above 98%. This high number gives us additional comfort that our data set is of high quality. Note that, in order to be eligible for inclusion in a portfolio, the stock needs to be included in the index. If a stock is in a portfolio and is taken out of the index, we still use its price return from the databases to calculate the portfolio return until the strategy excludes the stock from the portfolio.[14]

Table 2.1 shows information on return data per country and for the total market. The average monthly dollar return of the equally- and value-weighted frontier market portfolio equals 0.8%. The difference between these two is not statistically significant (t-value 0.4). Nevertheless, it suggests that small capitalization stocks outperformed large capitalization stocks in our sample. The average return in frontier markets is higher than in developed and emerging markets over this sample period, where the average equally-weighted returns are 0.5% and 0.6%, respectively.[15] The standard deviation of the equally-weighted frontier markets index return is 4.2%. This is marginally lower than the volatility of developed markets (4.4%) and substantially lower than the volatility of the emerging markets index (7.2%). Note that the low volatility in frontier markets is mainly due to low correlation among this group of countries. Individual country volatilities can be above 15% per month.[16] The local returns are somewhat higher with 1.4% per month for the equally-weighted, and 1.1% per month for the value-weighted index. Volatilities for local returns are approximately the same as for the returns in USD.

In addition, we present median market capitalizations in Table 2.1. We can see that the median firm size of frontier market stocks is USD 36 million. This is substantially lower than in emerging markets (EM) where the median firm size is approximately ten times larger at USD 337 million.

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[14] In most cases, stocks dropping from the index are not (immediately) delisted, limiting the concerns raised by Shumway (1997) on the potential effect of a delisting bias for US stock returns. For 20 individual stocks, we observe monthly returns below -90%, indicating severe stress for the companies involved. These negative returns are included in the portfolio returns. Nevertheless, despite extensive data checks, we cannot guarantee that there are some individual cases for which delisting returns are not accurately accounted for in our databases.

[15] The developed markets universe consists of stocks included in the FTSE World index and for emerging markets it is stocks in the S&P/IFCI Emerging Markets index.

[16] Erb, Harvey, and Viskanta (1996) predict the risk of equity markets in 135 countries. For the frontier markets, they predict 8-14% volatility on a monthly basis. This is roughly in line with our summary statistics in Table 2.1 for the individual countries.

2.2.3. Accounting data

For the firm characteristics book-to-market and earnings-to-price ratio, we use S&P as our first data source. If for a particular stock S&P data is not available, we use Worldscope data, which we lag with 6 months to account for delayed availability of the annual reports. We extract dividend yield data from the Interactive Data Exshare database, which we calculate as the cumulative daily dividend payments over the past twelve months, divided by the price at each month-end.

We check the data quality of each of these variables using various statistics, such as coverage, median, maximum value and minimum value in each month during our sample period. In addition, we examine alternative data sources, such as Bloomberg, in the case of suspicious values. This battery of quality checks has led to a unique, high-quality frontier emerging markets data set.

We summarize these firm characteristics of our sample data with statistics in Table 2.1. The median book-to-market ratio is 0.8 (EM 0.6), the median earnings-to-price ratio 8.5% (EM 6.1%) and the median dividend yield 2.5% (EM 1.7%). Based on these value characteristics, frontier market stocks are considered to have been cheaper than emerging markets stocks over this sample period. Kazakhstan and Panama do not have any dividend yield data, as they only entered the index in December 2007 and have a history of less than one year. Furthermore, for the entire sample of frontier markets, approximately one-third of the stocks have a dividend yield equal to 0%.

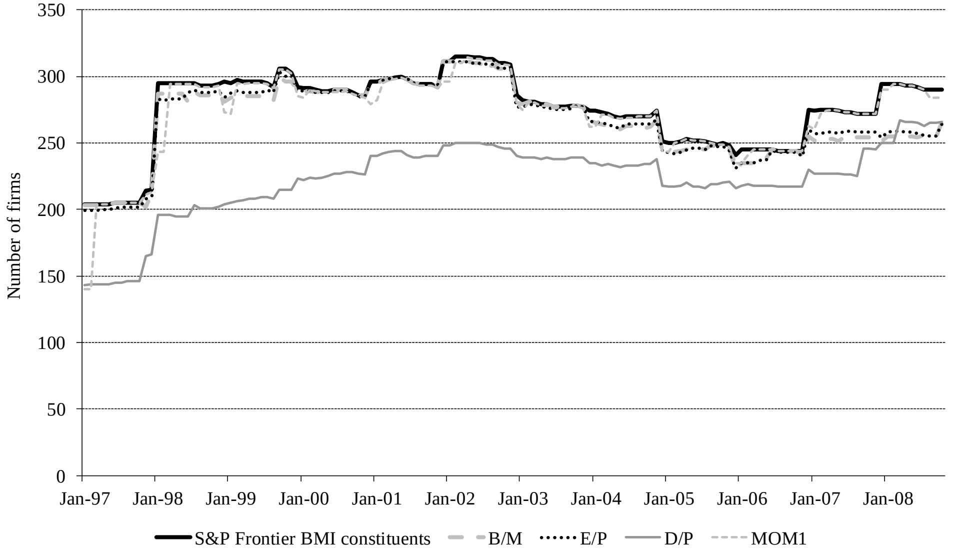
2.2.4. Data coverage of stock and firm characteristics

Figure 2.1 presents the number of S&P Frontier BMI constituents through time and the number of firms that have data available for the different characteristics. The number of index constituents is stable, with 204 at the start and varying between 250 and 300 over our sample period. There were 290 stocks at the end of the sample period in October 2008. Since stocks enter and exit the index, the total number of individual stocks over the entire sample period is slightly more than 1,400. For each stock, the market capitalization is available. For the return-related variables we show only the coverage of 1-month momentum, for which we have almost 100% data coverage.[17] The coverage of the book-to-market and earnings-to-price ratio is almost 100% before 2007, and slightly decreased thereafter, because our

[17] To prevent losing three years of our sample for the 36-month momentum and low-risk variables, we assume an expanding window in the beginning of our sample period starting with 12 monthly return observations.

data sources do not provide information for several stocks that newly entered the index. Dividend yield is the characteristic with the lowest data coverage, as it depends on a single data source. Nonetheless, dividend yields are available for at least 200 firms in most of the months of the sample period, meaning that the average coverage is above 80%. We conclude that the data coverage and quality is sufficiently high to examine the profitability of investment strategies in frontier markets.

FIGURE 2.1. Data coverage of stock and firm characteristics
The bold black line represents the number of firms in the S&P Frontier BMI. The other lines represent the data availability for the book-to-market ratio (B/M), the earnings-to-price ratio (E/P), the dividend yield (D/P), and 1-month momentum (MOM1).



2.2.5. Portfolio construction methodology

We form investment portfolios in a style similar to, e.g., Jegadeesh and Titman (1993). At the end of each month, we rank the stocks on a particular characteristic.[18] For our baseline strategy, we form an equally-weighted portfolio from the top 20% of the ranking, label this the Top portfolio, and compare these with the equally-weighted average return from the

[18] Note that we treat companies that pay no dividend at all separately when calculating the excess return for the D/P strategy. We treat them in the same way as firms with missing data and rank them in the middle, so that it does not appear in the top or bottom portfolio that month. This methodology of dealing with companies that pay no dividend and the empirical results are in line with Fama and French (1993).

entire sample, the Index portfolio. We additionally create an equally-weighted portfolio from the least attractive 20% of stocks, and label this the Bottom portfolio to investigate long-short strategies. For most frontier equity markets it is nearly impossible to short sell stocks. However, in a portfolio management context, the short portfolio can be used to underweight assets relative to the frontier market benchmark index. A lower portfolio weight than in the benchmark index means in essence a short position for the portfolio manager. Note that these short positions in the benchmark in this context are capped at the benchmark weight, while for long-short portfolios these weights are (in theory) uncapped. For small-cap stocks such long-only constraint is most problematic, as short positions relative to the benchmark are by definition small. For this reason, the main focus in all our analyses is on the top portfolio. Each month, new portfolios are constructed, which we hold for a period of twelve months, unless a stock gets delisted before the end of the holding period. These stocks exit the relevant portfolio, and the weights of the remaining stocks are adjusted proportionally.

As we construct new portfolios every month and use a 12-month holding period, at any point in time the strategies effectively hold stocks from twelve portfolios, each formed one month apart. We calculate monthly returns for a particular strategy as the average of the returns of the twelve portfolios. All returns are expressed in US dollars. For country- or region-neutral portfolios, we rank the stocks within each country on a characteristic and assign the top 20% of each country to the Top portfolio. Hence, the country-neutral Top portfolio has the same country distribution as the Bottom portfolio and the Index portfolio. An additional side-effect is that country-neutral portfolios contain the same percentage of stocks in a certain currency as the bottom or index portfolio and therefore the associated excess returns cannot be attributed to currency movements.

2.3. Value, momentum, size, and low-risk effects in frontier markets

In this section, we analyze the cross-section of returns on four common types of characteristics on which we have high-quality data available for our frontier emerging markets. First, we investigate three valuation characteristics, followed by an investigation of three momentum characteristics. We continue with firm size as measured by market capitalization and end with two low-risk characteristics. We continue the section by analyzing the impact of capital constraints on the results and conclude by investigating the diversification benefits between the three types of characteristics.

2.3.1. Value

We start by investigating value investment strategies for which Fama and French (1992) and Lakonishok, Shleifer, and Visney (1994) report significantly positive excess returns for US stocks. Fama and French (1998) and Rouwenhorst (1999) find out-of-sample evidence for international developed and emerging equity markets. We rank the cross-section of stocks in our sample on three value characteristics: the book-to-market ratio (B/M), earnings-to-price ratio (E/P), and dividend-to-price ratio (D/P). Stocks with high B/M, E/P, and D/P ratios have on average higher returns than stocks with low ratios. This is called the value effect. The left part of the results in Panel A of Table 2.2 indicates that our sample of frontier market stocks also exhibits strong value effects. The first row in Table 2.2 indicates that B/M sorted portfolios have a Top-Minus-Index (TMI) excess return of 0.74% per month, which is statistically significant with a t-value of 3.05.[19] For portfolios ranked on E/P, we find economically and statistically significant TMI returns of 1.26% per month with a t-value of 5.55. The D/P valuation strategy has the least positive excess returns, with 0.41% per month and a t-value of 1.72.

We also investigate the average return of Top-Minus-Bottom (TMB) portfolios. Table 2.2 shows that the documented excess return of the B/M strategy is almost equally split between the long and the short side, as the return of the B/M factor of 0.74% is roughly doubled to 1.66% when viewed in excess of the bottom portfolio. We find comparable results for E/P and D/P. Due to the increased volatility of this Top-Minus-Bottom strategy, the t-values increase to a lesser extent and decrease somewhat for E/P.

We compare our results to Top-Minus-Bottom returns of more developed equity markets. Fama and French (1998) report 0.64% excess return per month for B/M, 0.57% for E/P, and 0.46% for D/P for a global equity portfolio consisting of 13 countries over the period 1975 to 1995. They furthermore show that the value premium exists for most countries individually and are not limited only to the US. Rouwenhorst (1999) reports a 0.72% per month excess return for B/M for stocks in 20 emerging markets over the period 1987 to 1997, and Van der Hart, De Zwart, and Van Dijk (2005) report 0.73% and 0.68% per month excess return for B/M and E/P in 31 emerging markets over the period 1988 to 2004. Thus, the excess returns based on value-characteristics sorted investment strategies in frontier markets are economically at least as large as those reported in the literature for developed and emerging stock markets.

[19] Throughout our research, we use the method described in Newey and West (1987) to calculate t-values that are robust to heteroscedasticity and autocorrelation.

TABLE 2.2. Excess returns of portfolios sorted on value, momentum, size, and low-risk characteristics

At the end of each month between January 1997 and October 2008, all stocks in the S&P Frontier BMI for which the necessary information is available are ranked in descending order (apart from size and low-risk) according to their characteristics. B/M is the book-to-market ratio; E/P is the earnings-to-price ratio; D/P is the dividend-to-price ratio. MOM3, MOM6 and MOM12 are the past returns with formation periods of 3, 6, and 12 months. Size is the market capitalization of a stock and is ranked in ascending order, Beta is the 36-month historical covariance with the index return, and Volatility is the 36-month historical standard deviation of individual stock returns, both ranked in ascending order. The holding period is 12 months. The columns ‘Return’ contain the average monthly percentage excess returns of the equally-weighted top 20% portfolio minus the average returns of equally-weighted universe (index), except for rows with “top-minus-bottom” and “index-minus-bottom”. The corresponding t-values are presented next to the ‘Return’ columns. T-values are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). In panel A, the row “top-minus-bottom” contains excess returns of the top 20% versus bottom 20% portfolios. The row “index-minus-bottom” contains returns of the equally-weighted average of the universe minus the bottom 20% portfolio. The “EW and VW market risk adjusted” rows contains the alphas relative to a single-factor model with the equally-weighted (EW) and value-weighted (VW) frontier market index as the risk factor. The region (country) neutral results have the same number of stocks from each region (country) in the top-minus-index portfolios. Finally, the last row indicates the results for the countries with a low individualism score. In panel B, the sample is split in halves from the most and least liberalized countries according to three definitions of liberalization (Heritage Foundation (HF), ETH Zurich (KOF), and Fraser Institute (EFW)). The split is in such a way that at each point in time about half the stocks are in the sample that is most liberalized, and half that is least liberalized. Country neutrality is only applied to the size portfolio in panel B.

	B/M		E/P		D/P		MOM3		MOM6		MOM12		Size		Beta		Volatility	
	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*
Panel A. All stocks																		
Top-Minus-Index	0.74	*3.05*	1.26	*5.55*	0.41	*1.72*	0.95	*6.52*	0.77	*4.02*	0.59	*3.08*	0.23	*0.81*	-0.32	*-0.89*	0.07	*0.26*
Top-Minus-Bottom	1.66	*4.49*	1.58	*4.52*	0.78	*2.78*	1.69	*4.69*	1.19	*2.80*	0.87	*2.52*	0.51	*1.19*	-0.59	*-0.32*	-0.21	*-0.12*
Index-Minus-Bottom	0.92	*4.07*	0.33	*1.52*	0.37	*2.10*	0.74	*2.85*	0.42	*1.57*	0.28	*1.37*	0.27	*1.47*	-0.27	*-0.61*	-0.28	*-0.73*
EW Market risk adjusted	0.69	*3.21*	1.21	*5.56*	0.59	*3.00*	0.97	*6.01*	0.74	*3.22*	0.53	*2.62*	0.22	*0.74*	0.12	*0.44*	0.41	*1.97*
VW Market risk adjusted	0.74	*3.12*	1.24	*5.55*	0.50	*2.43*	0.96	*6.14*	0.73	*3.35*	0.55	*2.78*	0.30	*1.07*	-0.02	*-0.06*	0.24	*1.04*
Region neutral	0.73	*3.51*	1.08	*5.03*	0.56	*3.89*	0.73	*6.63*	0.69	*5.51*	0.46	*2.87*	0.81	*3.64*	0.03	*0.12*	-0.26	*-1.12*
America	1.18	*2.80*	0.63	*1.48*	0.78	*2.36*	0.35	*2.04*	0.31	*1.43*	0.13	*0.49*	0.72	*1.49*	0.73	*1.92*	-0.09	*-0.19*
Europe	1.02	*2.31*	0.92	*2.20*	-0.43	*-0.94*	0.55	*3.25*	0.56	*2.92*	0.35	*1.18*	1.18	*2.66*	-0.12	*-0.12*	0.04	*0.04*
Africa	0.27	*1.28*	1.12	*3.33*	0.89	*3.74*	0.93	*5.05*	0.94	*4.43*	0.80	*2.82*	0.72	*2.64*	0.18	*0.63*	-0.47	*-2.08*
Asia	-0.25	*-0.58*	0.50	*1.61*	-0.31	*-1.00*	0.70	*2.90*	0.63	*2.19*	0.70	*2.26*	-0.33	*-1.06*	-0.14	*-0.40*	0.23	*0.77*
Country neutral	0.40	*3.09*	0.56	*3.40*	0.21	*1.91*	0.26	*3.42*	0.21	*2.05*	0.12	*0.92*	0.47	*2.58*	-0.41	*-2.19*	-0.29	*-2.07*
Low Individualism	-	-	-	-	-	-	1.15	*4.80*	0.94	*3.32*	0.85	*2.87*	-	-	-	-	-	-
Panel B. Capital constraints																		
HF: Most liberalized	1.03	*3.18*	0.87	*3.29*	0.29	*0.99*	0.90	*5.85*	0.82	*5.47*	0.66	*3.60*	0.42	*2.38*	0.30	*0.94*	0.04	*0.12*
Least liberalized	0.67	*1.62*	1.66	*4.14*	0.15	*0.48*	1.06	*4.50*	0.84	*2.93*	0.44	*1.49*	0.66	*2.36*	-0.92	*-2.10*	-0.07	*-0.17*
KOF: Most liberalized	0.93	*2.56*	0.70	*2.15*	0.14	*0.46*	0.83	*5.16*	0.71	*4.02*	0.50	*2.44*	0.39	*1.98*	0.05	*0.15*	-0.09	*-0.29*
Least liberalized	0.48	*1.44*	1.68	*5.33*	0.64	*2.48*	1.02	*4.85*	0.79	*2.90*	0.61	*2.11*	0.52	*1.95*	-0.64	*-1.57*	0.02	*0.05*
EFW: Most liberalized	0.84	*2.56*	0.64	*1.98*	-0.21	*-0.61*	0.82	*5.31*	0.77	*4.57*	0.54	*2.60*	0.61	*3.07*	0.39	*1.15*	0.22	*0.66*
Least liberalized	0.64	*1.81*	1.56	*4.82*	0.34	*1.18*	0.99	*5.10*	0.76	*2.92*	0.52	*2.11*	0.38	*1.63*	-0.62	*-1.56*	-0.01	*-0.02*

As our results might be driven by frontier market risk, we also calculate the alphas relative to a single-factor model with the equally- or value-weighted frontier market index as the single risk factor. The betas of the TMI strategies are close to zero for each of the value strategies (not reported). This implies that the alphas reported in Table 2.2 ('market risk adjusted') here are close to the raw TMI returns reported before. For example, the 0.74% raw excess return of the B/M strategy is slightly reduced to a significant risk-adjusted alpha of 0.69% per month when we use an equally-weighted market index and stays 0.74% per month when we use a value-weighted market index. An important exception is the D/P strategy. This strategy selects stocks with a relatively low beta to the market index.[20] Hence, the market risk-adjusted excess return is 0.59% (t-value 3.00) per month for an equally-weighted index and 0.50% (t-value 2.43) per month for a value-weighted index, whereas the raw excess return was only 0.41% (t-value 1.72). Summarizing, our results indicate that unconditional beta risk cannot explain the excess returns on the investment strategies. This observation is in line with results documented for these strategies in developed and emerging equity markets.

As these investment strategies rank all stocks at each period in time, the raw results reported in the first row of Panel A of Table 2.2 might be influenced by regional effects. In other words, the top portfolio might be more exposed to certain regions than the index which could explain part of the abnormal returns. Therefore, we also calculate each of the investment strategies per region and also display the region-neutral TMI investment strategies in the second part of Table 2.2. These investment strategies require the 20% most attractive stocks from each region to be in the top portfolios, which ensures that the regional distribution of the top portfolio is equal to the index.[21] The results in Table 2.2 indicate that the results are not driven by regional effects. The region-neutral strategy yields value returns of 0.73% (B/M), 1.08% (E/P), and 0.56% (D/P) per month, which are all statistically significant and similar in magnitude as the non-neutral returns. We document a positive TMI return for most of the valuation characteristics of each of the regions separately. The D/P strategy seems to be the weakest valuation variable where both Europa and Asia have negative returns. These low returns for the long-only D/P strategy is caused by its low beta, as we also saw for the non-neutral strategy. Summarizing our region-neutral results, we conclude that the presence of the value effect is robust to regional influences.

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[20] Fama and French (1998) also report that the global high D/P strategy has a beta of 0.87, lower than the beta of the B/M and E/P strategy, which are 0.94 and 0.95, respectively.

[21] The number of stocks is not exactly equal with or without region or country neutrality imposed, as we require each region or country to have at least 4 stocks available and data coverage of at least 40% at a point in time to be included in the analysis. The average number of stocks in the strategy per region is as follows: America 35, Europe 103, Africa 80, Asia 49.

While the value effect is present across regions, it is possible that differences in country-specific accounting standards or currency effects might drive our results, at least to some extent. Therefore, we take the analysis one step further and calculate country-neutral investment strategies. In this way, country and currency effects are hedged out relative to the index, as explained in Section 2.2.5 on the portfolio construction methodology. Table 2.2 shows that imposing country neutrality does not alter our conclusions about the significant presence of value effects in frontier markets. Nevertheless, part of the global TMI returns can be attributed to country allocation, as TMI returns for the country-neutral strategy are about half of the non-country-neutral returns. Our finding that part of the value effect is driven by country allocation is in line with Asness, Moskowitz, and Pedersen (2013), who report that ranking country indexes based on valuation measures leads to significant excess returns. This analysis shows the benefits of using stock-specific data as our results indicate that valuation measures at the individual stock level contain information above and beyond the country level which is vital to fully capture the factor return.

The analyses in this sub-section show that the value effect is robust and strongly present in our data set consisting of frontier emerging equity stocks.

2.3.2. Momentum

In this sub-section, we investigate the profitability of momentum strategies in frontier emerging markets. This means that stocks in the cross-section are ranked on their past returns. Stocks with higher past returns are expected to have higher future returns. Jegadeesh and Titman (1993) report significantly positive excess returns for winner stocks relative to loser stocks over the past 3 to 12 months in the US, and Rouwenhorst (1998, 1999) confirms these findings for international developed and emerging market stocks.

In Table 2.2 we display momentum strategies with a look-back period of 3, 6, and 12 months, and a holding period of 12 months. Similar to the value strategies, we choose a relatively long holding period of 12 months as we know that transactions costs can be substantial in frontier emerging markets.[22] We see that the 3-month look-back period results in a 0.95% per month excess return relative to the index. For longer look-back periods the excess returns are smaller, with 0.59% per month for a 12-month look-back period. In order to compare our results to the literature, we also display how much excess returns the short positions generate and how this adds up to returns of the Top-Minus-Bottom portfolios. In all cases, the results are stronger for the top than for the bottom portfolio. TMB returns are

[22] In Section 2.4 we investigate the sensitivity of value and momentum effects to other holding periods.

higher than for TMI, but with lower t-values. For the 6-month momentum strategy, e.g., we obtain a 1.19% per month excess return with a t-value of 2.80 for the TMB portfolio compared to an excess return of 0.77% per month with a t-value of 4.02 for the TMI portfolio.

The magnitude of our momentum profits in the medium term is in line with those observed for developed and emerging markets. Jegadeesh and Titman (2001) report an excess return of 1.09% per month for past 6-month winners relative to losers for the US over the period 1965 to 1997. Rouwenhorst (1998, 1999) documents 1.16% per month for European stock markets (1980-1995) and 0.39% per month for emerging markets (1982-1997). Van der Hart, De Zwart, and Van Dijk (2005) report 0.74% for their sample of 31 emerging markets over the period 1988 to 2004. The short-term momentum returns are in line with Chan, Hameed, and Tong (2000), who report a 1.1% per month excess return for short-term country momentum strategies using a sample of 23 developed and emerging countries over the period 1980 to 1995. We conclude that the excess returns from our frontier equity markets momentum strategies are economically at least as strong as those reported previously for developed and emerging equity markets.

We also calculate the alphas relative to a single-factor model with the equally-weighted and value-weighted frontier market index as the risk factor. The betas of the TMI strategies are close to zero for each of the excess returns of the momentum strategies (not reported). This implies that the alphas reported in Table 2.2 are about the same as the raw TMI returns reported before. Hence, these results indicate that unconditional beta risk cannot explain the excess returns of the momentum investment strategies. This is in line with results documented for momentum strategies in developed and emerging equity markets.

In the second part of Panel A, Table 2.2 we investigate in more detail the influence of regional and country effects on the return of momentum strategies. We see that the raw momentum returns slightly decrease when we impose region neutrality. For example, the 6-month momentum strategy decreases from 0.77% per month to 0.69% per month. For all momentum strategies, each of the regions separately also have a positive excess return. Particularly for the 6-month momentum strategy we find the strongest results for Africa (0.94% per month) and the weakest for America (0.31% per month). Imposing country neutrality further reduces the momentum profits, although only for the 12-month momentum strategy we do not find significant results anymore. The 6-month momentum profits reduce to 0.21% per month, implying that country momentum is part of the total momentum profit. Rouwenhorst (1998), Chan, Hameed, and Tong (2000) and Bhojraj and Swaminathan (2006) provide empirical evidence of momentum profits at the country level for developed and emerging equity markets. Our results confirm the existence of country momentum within the group of frontier markets and may serve as out-of-sample evidence for what is sometimes called macro-momentum, since it is at the country level.

Chui, Titman, and Wei (2010) link the existence of the momentum effect to the degree of individualism of investors within a country.[23] Their results suggest that countries with a high Hofstede score on individualism also earn higher average momentum returns.[24] For several of the frontier markets countries, a score on individualism is available; see Hofstede (2001) and Appendix 2.B. The average score is low for frontier markets for which the score is available. A low score suggests that social groups such as families play a more important role than individuals. Chui, Titman, and Wei (2010) claim that the medium-term momentum effect is weaker for countries with low individualism. The low individualism score for frontier markets would imply that momentum effects in these markets are rather small. Hence, we investigate the momentum returns for the sub-sample of countries with a low individualism score. Estonia, Jamaica, Lebanon, and Slovakia are excluded because they have an individualism score above the threshold of the low individualism sub-sample from Chui, Titman, and Wei (2010). From the last row of Panel A in Table 2.2, we observe that the momentum returns from our low individualism sub-sample are at least as high as those in the full sample. Hence, our results do not seem to indicate that momentum is weak in countries with a low score on cultural individualism.

The analyses in this sub-section show that the momentum effect is robust and strongly present in our data set consisting of frontier emerging equity stocks.

2.3.3. Size

The size effect means that the cross-section of stocks is ranked according to market capitalization of equity. Stocks with a relatively low market capitalization experience higher returns than stocks with a relatively large market capitalization. The existence of the size effect has been first documented by Banz (1981) for US equity markets and has later been confirmed by many other researchers in equity markets around the world. Van Dijk (2011) provides a comprehensive review on the size effect around the world.

Panel A of Table 2.2 indicates that we do not find a size effect among the total group of frontier emerging markets countries. The excess return of a portfolio of stocks with a small market capitalization relative to the index is an insignificant 0.23% per month. Also,

[23] Speidell (2009) reports some anecdotal evidence of differences in investor behavior in frontier markets.

[24] See www.geert-hofstede.com for detailed information on the scores on different aspects of culture.

small capitalization stocks do not significantly outperform large capitalization stocks, as the return of the Top-Minus-Bottom portfolio is 0.51% with a t-value of 1.19.

Our results on a region and country-neutral level indicate that the size effect is a local effect. In three out of four regions the return of small stocks is higher than that of the index. Due to diversification benefits across regions, the region-neutral size effect is economically and statistically significant with an excess return of 0.81% per month and an associated t-value of 3.64. Imposing country-neutrality leads to qualitatively similar results as imposing region-neutrality. The finding of only a local size effect again emphasizes the need of individual stock data to fully capture the return premium related to the size factor, as the country allocation decision does not seem to add significant value.

These results are in line with the empirical literature on the international existence of the size effect. For example, Heston, Rouwenhorst, and Wessels (1999) report a significant size effect in Europe, which is due to small stocks within a country earning higher risk-adjusted returns than large stocks within the same country. Barry, Goldreyer, Lockwood, and Rodriguez (2002) also only find evidence of a size effect in emerging markets when they measure size relative to the local market. The size effect in Rouwenhorst (1999) is significant in 12 out of 20 individual emerging markets.

The analyses in this sub-section show that only the local size effect is present in our data set consisting of frontier emerging equity stocks. For that reason we only focus on the local size factor in the remainder of the analyses.

2.3.4. Low-risk

Another factor that is difficult to reconcile with the CAPM is the low-risk effect. This factor is constructed by ranking stocks on historical risk measures, such as beta or volatility. To our knowledge, Black, Jensen, and Scholes (1972) are the first to document the abnormal returns of these low-risk portfolios. Later, Blitz and Van Vliet (2007) documented that low-risk stocks have alpha relative to the CAPM not only in the US, but also in international markets. There are at least three explanations put forward for the existence of the low-risk effect. First, investors might not be allowed to or willing to apply leverage to their investment portfolio. When they wish to increase expected returns without employing leverage they are forced to buy high-risk stocks (under the assumption that expected returns and risk are positively correlated); see Black (1972), Falkenstein (2009), and Baker, Bradley, and Wurgler (2011). Second, the existence of the low-risk effect might be caused by a two-step investment process. In the first step the asset allocation decision is taken by the chief investment officer using absolute risk and return criteria. In the second step, investment managers are hired to outperform a benchmark, causing them to focus on relative risk and return criteria. Such delegated portfolio management decisions may lead to suboptimal portfolios and may distort aggregate asset prices in such a way that high-risk assets are structurally overpriced and low-risk assets structurally underpriced; see Van Binsbergen, Brandt, and Koijen (2008). Thirdly, Shefrin and Statman (2000) suggest that private investors may hold part of their wealth, above a certain threshold level, as a gamble to quickly become rich. This might explain why many private investors only hold a limited number of stocks in their portfolio. This behavioral effect might lead highly volatile stocks to be overpriced.

In Panel A of Table 2.2, we display the returns of a portfolio of low-beta stocks and low-volatility stocks. For the TMB portfolio this is the low-beta (low-volatility) portfolio minus the high-beta (high-volatility) portfolio. Both risk measures beta and volatility are calculated using historic 36 month returns. The empirical results in Table 2.2 indicate that we do not find a strong low-risk effect in frontier emerging markets countries. The excess return of a portfolio of stocks with a low-volatility relative to the index is an insignificant 0.07% per month, whereas low-beta stocks underperform the index by an insignificant 0.32% per month. As risks are persistent, portfolios formed on low-risk characteristics are also in the investment period less risky than the index. Hence, it makes more sense to look at risk-adjusted returns than absolute levels of return. We see that the low-volatility effect, with an alpha of 0.41% per month relative to the equally-weighted index, is economically and statistically significant. However, this result is not robust. For other specifications, for example using low-beta instead of low-volatility or measured against a value-weighted index, the results are not statistically significant. For our region- or country-neutral analyses, we occasionally find a significantly positive relation between risk and return as one would expect from standard textbook finance.

Blitz, Pang, and Van Vliet (2013) suggest that low-risk strategies also earn higher risk-adjusted returns in emerging equity markets. However, they observe that in the first half of their sample (1989-1999) the low-risk effect in emerging markets is weaker than in the second half of their sample (2000-2010). They attribute this to the lack of benchmark-driven investors in the first half of their sample. We expect that for frontier markets over our sample period the number of benchmark-driven investors is limited, and only recently has started to become an asset class that institutional investors might allocate to. If the conjecture of Blitz, Pang, and Van Vliet (2013) is correct, we also expect a small low-risk effect in our sample. Our results seem consistent with their explanation. This means that our findings casts doubt on the explanation that the low-risk effect is caused by market frictions such as short sales constraints, which are more likely to exist in frontier markets.

The analyses in this sub-section show that the low-risk effect is neither statistically nor economically significant in our sample of frontier emerging equity stocks. For that reason, we only analyze the value, momentum and local-size strategies in subsequent sections.

2.3.5. Influence of capital constraints

The empirical results on the value, momentum, and local size effect that we displayed in Table 2.2 could be related to capital constraints in frontier equity markets, as these markets have not always been as open as they currently are. Although our data provider takes these requirements into account before admitting a country to the frontier markets index, the investment strategies could potentially still be tilted towards countries with the most or least investment restrictions in our sample.[25] Although *a priori* it is not clear what the effect would be of this tilt, we want to make sure that our findings are robust in this respect. Therefore, we use data on financial market liberalization to separate the frontier markets into a most and least liberalized group and verify whether our results still hold for these sub-samples.[26]

We use three different measures of financial market liberalization, namely relevant sub-indices of the Index of Economic Freedom reported by The Heritage Foundation (HF)[27], the KOF Index of Globalization constructed by the ETH Zurich (KOF)[28] and the Economic Freedom of the World (EFW) reported by the Fraser Institute.[29] We choose sub-indices in such a way that they best represent investment freedom.[30] The higher the score, the higher the financial liberalization, meaning it is less likely that capital constraints play an important role in that country. We omit scores when a country is not yet included in the S&P Frontier BMI. For all three indices the coverage is high, although not all data is always available, such as KOF and EFW data for Lebanon. As can be expected, the rank correlations between

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[25] Note that unreported empirical results indicate that the average returns of the frontier emerging markets are not related to their average financial market liberalization score or the change thereof.

[26] See Bekaert and Harvey (2003) for an overview on integration and liberalization measures for emerging markets. Unfortunately, Bekaert and Harvey (1995, 2000) do not have integration data available for the frontier equity markets in our sample.

[27] Data are available at http://www.heritage.org. We use the average of the sub-indices Financial Freedom and Investment Freedom, as these two are closest to the definition of freedom that we prefer to measure for our analyses.

[28] Data available at http://globalization.kof.ethz.ch. For more details on this index: see Dreher (2006). We use the Economic Globalization dimension scores, as the Political and Social Globalization dimensions are less relevant for our analyses.

[29] Data from the Fraser Institute available at http://www.freetheworld.com. We use the area Freedom to Trade Internationally as this area most directly represents the measure we are interested in.

[30] Appendix 2.A contains the annual scores per frontier country and a comparison of the liberalization measures for frontier markets with developed and emerging countries.

these indices are relatively high with roughly 75% over the sample period. Nevertheless, some differences are present and therefore we investigate the impact of each of the three measures separately.

At the end of each month, we rank all countries based on each of the three financial liberalization indices.[31] We choose the thresholds to split the countries into a most and least liberalized group in such a way that the two groups contain approximately an equal number of stocks. We then form investment portfolios on the most and least liberalized stocks separately. Panel B of Table 2.2 contains the results for the sub-samples with the highest and lowest financial liberalization according to each of these measures. With the exception of the D/P factor, which also showed the weakest overall results, we observe that value strategies still deliver significantly positive excess returns in liberalized as well as non-liberalized countries, both from an economic and statistical point of view. Therefore, we conclude that capital constraints do not seem to drive the value effects. We also check the influence of capital constraints of each of the countries on our momentum results and on the country-neutral size results. These strategies all still deliver substantial positive excess returns in both liberalized and non-liberalized sub-samples.[32] Therefore, we also conclude that capital constraints do not seem to drive momentum and size returns.

2.3.6. Diversification effects

Asness, Moskowitz, and Pedersen (2013) indicate that value and momentum strategies are negatively correlated within asset classes. This negative correlation implies diversification benefits from combining value and momentum effects in one investment strategy. We therefore investigate the correlation between the three value strategies, the three momentum strategies, and the local size strategy that we analyzed before.

[31] We incorporate appropriate time lags when using the index scores. Heritage Foundation informed us that annual scores have become available in the first quarter. Therefore we use the scores as of the end of March every year. KOF data has become available every year around January based on data of two years ago. So, around January 2008, the new index became available based on 2005 data. To be conservative, we use a two years and one quarter lag, meaning we assume 2005 data is available at the end of March 2008. Note that this index contains a look-ahead bias, as data of previous years changes with the introduction of a new methodology. The same holds for EFW, although data becomes available a bit earlier. We use a one year and three quarters lag, meaning that we assume 2005 data is available at the end of September 2007.

[32] Our proxies are related to capital constraints, which could be related to more practical difficulties for international investors. These measures of capital constraints could therefore also be interpreted as efficiency measures. Griffin, Kelly, and Nadari (2010) suggest that traditional return-based efficiency measures, such as variance-ratio tests, are not related to the magnitude of momentum returns in 56 developed and emerging markets.

TABLE 2.3. Correlation between value, momentum, and size strategies in frontier markets
The table contains the correlations between the monthly top-minus-index excess returns of the value, momentum, and size strategies in frontier emerging markets. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio.

	Value			Momentum			Size
	B/M	E/P	D/P	MOM3	MOM6	MOM12	Size
B/M	1	0.47	-0.33	0.18	-0.17	-0.25	0.23
E/P		1	0.00	0.20	0.03	-0.21	0.01
D/P			1	-0.18	-0.12	-0.09	-0.26
MOM3				1	0.51	0.35	-0.03
MOM6					1	0.75	-0.07
MOM12						1	-0.07
Size							1

In Table 2.3, the correlations over the period 1997 to 2008 are displayed. The momentum strategies are all positively correlated, ranging from 0.35 to 0.75 for different formation periods. The correlation between valuation strategies is mixed. B/M and E/P strategies are positively correlated with a coefficient of 0.47. The D/P strategy is negatively correlated to the B/M strategy and uncorrelated to the E/P strategy. Our empirical results suggest that combining different valuation indicators improves the risk-adjusted performance of a long-only valuation investment strategy.

The off-diagonal block of the correlation matrix indicates that valuation strategies are on average unrelated to the momentum strategies with correlations ranging from -0.25 between B/M and 12-month momentum to 0.20 between E/P and 3-month momentum. Hence, the diversification benefits between value and momentum within frontier markets are large. The size strategy is also virtually uncorrelated with value and momentum strategies, indicating that diversification benefits also exist with the size factor.

2.4. Incorporating transaction costs

The results in the previous section are based on market prices without taking transaction costs explicitly into account. Fortunately, our data provider S&P explicitly takes liquidity into account when deciding to include a country or a stock in their frontier markets index. Hence, we expect that the stocks in our sample can be traded in reasonable quantities.[33] Furthermore, our results in Sub-section 2.3.5 already indicate that for our sample of stocks, constraints on the free movement of capital into frontier countries does not explain the

[33] See Lesmond (2005) and Bekaert, Harvey, and Lundblad (2007) for a detailed investigation of liquidity in emerging markets.

existence of the value and momentum effects. Nevertheless, actual transaction costs, such as bid-ask spreads, market impact costs and commissions might be a particular issue for frontier markets, as liquidity is typically lower than for more developed equity markets (see, e.g., Speidell and Krohne 2007) as indicated in Table 2.1. This raises the question on whether the abnormal returns associated with value and momentum investment strategies are truly inconsistent with market efficiency. In this section we analyze the profitability of the investment strategies when faced with real life market imperfections.

Not much has been documented on actual trading costs in frontier markets. Papers that examine stock market anomalies after incorporating trading costs in U.S. markets often make use of the model of Keim and Madhaven (1997), see e.g. Avramov, Chordia and Goyal (2006). However, as this model is only calibrated on the U.S. market it can therefore not be applied to frontier markets. Recently, Marshall, Nguyen, and Visaltanachoti (2013) estimated the transactions costs for a sample of 19 frontier markets stocks using data over the period 2002 to 2010 from Thomson Reuters Tick History database. They report average value-weighted effective spreads of 0.95% and market impact costs of 0.45% over their sample period.[34] Furthermore they use commission data based on Quisenberry (2010) which the author estimates to be 1.09% on average in 2007. We therefore assume total single-trip transaction costs of 2.5% for each stock in our analysis which is equal to the sum of the spread between mid and bid/ask price, market impact, and commission costs. This estimate for frontier emerging markets is substantially larger than recent estimates for more developed equity markets. E.g., De Groot, Huij and Zhou (2012) report average transaction costs estimates incorporating spread, market impact and commissions of 9 basis points for S&P 500 stocks over the period 1990 to 2009 and 26 basis points for the 600 largest European stocks over the same sample period. This means that our assumption of transaction costs is 28 times larger than the US estimates and 10 times larger than the European estimates. Although our sample seems to be more liquid than that of Marshall, Nguyen, and Visaltanachoti (2013), we prefer to be conservative and apply these cost estimates only to the largest 150 stocks in our sample. In Figure 2.1 we showed that our sample consists of approximately 300 stocks at each point in time, which means that we disregard the smallest half of our sample in our analysis in this section. An additional important trading cost component in frontier markets are opportunity costs, since finding a counterparty to trade with might not be that easy in frontier markets. As a consequence, we therefore skip one

[34] In addition, we asked a large stock broker (Nomura) for estimates on bid-ask spreads in frontier markets. They find that these spreads are generally below 1%, confirming the results by Marshall, Nguyen, and Visaltanochoti (2011).

month between ranking and portfolio formation. This means that an investor may spend a whole month searching for a counterparty to trade with.

The results in Table 2.4 incorporate transaction costs in the value and momentum investment strategies. We do not include the size effect here for two important reasons. First, the size effect is defined as the excess returns of small caps versus large caps. We focus on the largest 150 stocks in our analysis after transactions costs, which excludes investigating the small-cap effect as this requires trading in the smallest stocks of our sample. Second, our estimates on transaction costs are conservative for our sample of large-cap stocks. It is less clear what the trading costs in practice may be for a portfolio of small-cap stocks. Hence, we decide to focus only on value and momentum strategies in this section.

Panel A of Table 2.4 contains the results based on a 12-months holding period. The first row in the panel contains the gross returns of each of the effects based on the sample of 150 largest stocks and with a one-month skip between ranking and implementation. Although these raw returns are slightly smaller in magnitude compared to those reported in Table 2.2 on the entire sample and without assuming an implementation lag, the returns are still statistically significant. For example, the B/M strategy yields a 0.66% per month excess return versus a 0.74% that we saw before on the entire sample. Hence, the gross returns are somewhat smaller in magnitude as we reported before, but are less likely to incur substantial transactions costs. Only for dividend yield we find a significant improvement from 0.41% per month (t-value of 1.72) to 0.74% per month (t-value of 3.47). Omitting the small-cap stocks from our analysis leads to a larger beta of the D/P strategy compared to our results on the whole sample reported in Sub-section 2.3.1.

The remainder part of Panel A of Table 2.4 contains the excess returns of the top portfolio after incorporating transaction costs compared to the equally-weighted index return. More precisely, at the end of every 12-month holding period we investigate which stocks exit and enter the portfolio, multiply this total turnover weight by 2.5% single-trip trading costs and subtract it from the gross return of that portfolio in that month. The second row in the panel assumes a theoretical equally-weighted index that we assume can be invested in against zero costs. However, more realistic would be to evaluate the profitability of anomalies against an index net of transaction costs which could be seen as the passive alternative of the trading strategies. The third row in the panel displays the excess returns of the strategies relative to the index return where we assume that stocks entering and leaving the index also incur the same transactions costs as for the stocks in our trading strategies. The one-way turnover of the benchmark is relatively high with approximately 2.5% per month which leads to about 12 basis points difference in returns between the gross and net benchmark.

TABLE 2.4. Excess returns of value and momentum portfolios before and after trading costs

The table reports gross and net excess returns of value and momentum portfolios. All portfolios are formed as described in Table 2.2, except that the sample only contains the largest 150 stocks in each month and one month is skipped between ranking and portfolio formation. The gross returns are the top-minus-index excess returns. The net returns are calculated as gross returns minus portfolio turnover multiplied by 2.5% single-trip trading costs. Two types of index returns are chosen to calculate the net excess portfolio returns. One is the gross index return, and another is the index return net of transaction costs caused by index turnover. Monthly single-trip portfolio turnovers are presented in percentages. The turnover caused by index changes is taken into account as part of portfolio turnover. Portfolios with holding periods of 12 months, 6 months, 18 months, and 24 months are reported, respectively.

	B/M		E/P		D/P		MOM3		MOM6		MOM12	
	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*
Panel A: 12-month holding												
Gross	0.66	*3.27*	0.78	*3.34*	0.74	*3.47*	0.79	*5.42*	0.57	*2.88*	0.35	*1.68*
Net (gross index)	0.44	*2.18*	0.52	*2.20*	0.52	*2.41*	0.48	*3.12*	0.26	*1.34*	0.04	*0.21*
Net (net index)	0.56	*2.77*	0.64	*2.73*	0.64	*2.99*	0.60	*3.99*	0.39	*1.95*	0.16	*0.80*
Turnover	4.88		5.58		4.77		6.84		6.78		6.76	
Panel B: 6-month holding												
Gross	0.50	*2.37*	0.74	*3.00*	0.77	*3.47*	0.97	*5.35*	0.92	*3.68*	0.65	*2.67*
Net (gross index)	0.15	*0.72*	0.34	*1.36*	0.43	*1.88*	0.34	*1.76*	0.32	*1.28*	0.19	*0.82*
Net (net index)	0.33	*1.54*	0.51	*2.05*	0.60	*2.67*	0.51	*2.70*	0.49	*1.97*	0.37	*1.53*
Turnover	7.31		8.36		7.15		13.17		12.67		9.64	
Panel C: 18-month holding												
Gross	0.67	*3.37*	0.75	*3.40*	0.64	*3.05*	0.51	*3.70*	0.32	*1.80*	0.24	*1.35*
Net (gross index)	0.51	*2.59*	0.57	*2.53*	0.49	*2.29*	0.30	*2.02*	0.11	*0.60*	0.03	*0.19*
Net (net index)	0.60	*3.04*	0.66	*2.96*	0.58	*2.73*	0.39	*2.71*	0.20	*1.12*	0.12	*0.70*
Turnover	3.59		4.12		3.55		4.88		4.86		4.76	
Panel D: 24-month holding												
Gross	0.63	*3.27*	0.73	*3.30*	0.53	*2.60*	0.49	*3.86*	0.27	*1.62*	0.14	*0.83*
Net (gross index)	0.51	*2.68*	0.60	*2.67*	0.41	*2.00*	0.34	*2.55*	0.12	*0.72*	-0.01	*-0.03*
Net (net index)	0.58	*3.04*	0.67	*3.01*	0.49	*2.37*	0.41	*3.17*	0.19	*1.16*	0.07	*0.39*
Turnover	2.88		3.20		2.82		3.60		3.61		3.65	

When we focus on the value strategies with a 12-month holding period we observe in the last row of the panel that the one-way turnover is ranging from 4.8% to 5.6% per month (or 57% to 67% per year), indicating that not all stocks have to be traded at the end of the holding period. Some value stocks remain value stocks, not inducing a trade after 12 months. This turnover leads to a decrease in returns of 10 to 14 basis points per month when compared to a net benchmark and 22 to 26 basis points per month when compared to a gross benchmark. Still, we observe economically and statistically significant returns of approximately 6.6% to 7.7% per annum after incorporating transactions costs compared to a net benchmark.[35] Momentum returns are less robust to transactions costs than valuation strategies. The turnover of these strategies is higher than for valuation strategies with almost 7% per month (or around 80% per year), and in combination with lower gross excess returns the 12-month momentum strategy is no longer statistically significant. However, also the net returns of 4.6% and 7.2% per annum for the 6-month and 3-month momentum strategy, respectively, compared to a net index indicates that also these strategies are economically and statistically significant.

In addition to the 12-month holding period, Table 2.4 also contains the after transaction costs returns of the same investment strategies with holding periods ranging from 6 months to 24 months in Panel B to D. Shorter holding periods imply more aggressive trading when a stock drops out of the top 20% portfolio. However, gross returns are also likely to be higher. We investigate the trade-off between turnover and gross returns by examining the net returns of the strategies with different holding periods. Since valuation characteristics do not change significantly over time, we see that the turnover increases to approximately 7% to 8% per month for a 6-month holding period, and declines to approximately 3% for a 24-month holding period. Simultaneously, we observe that the gross returns of the value strategies remain relatively stable for different holding periods. This analysis indicates that the holding period matters for the net returns of an investor. Investors that try to capture the value effect in frontier markets might prefer to hold stocks somewhat longer than the 12 months that we use in our standard analysis, as net returns do not seem to decrease for longer holding periods. Momentum strategies are more dynamic by nature, which results in higher trading activity for shorter holding periods. A strategy with a 6-month formation and holding period yields 12.7% turnover per month. This eats up about one half of the gross excess returns. Holding periods longer than 12 months lead to lower turnover, but also to lower gross returns, which results in lower net returns. We find that only momentum strategies with a 3-month formation period remain economically and statistically

[35] This is at odds with Houge and Loughran (2006), who suggest that the value effect is driven by stocks with little liquidity and hence cannot be exploited by investors.

significant for holding periods longer than one year. We conclude based on this analysis, that the optimal holding period for momentum strategies is around 6 to 12 months.

The findings above indicate that the value and momentum effects still exist when incorporating conservative assumptions of transaction costs and therefore seem to be inconsistent with market efficiency. Note that we assume the same transaction costs for each of the 150 largest stocks in our sample, while it could be the case that, e.g., momentum stocks are more expensive than the average stock (see, e.g., Korajczyk and Sadka (2004) and Lesmond, Schill, and Zhou (2004)). Since we do not have transactions costs data on individual stocks, we cannot undertake such analysis in this study. We leave this as a topic for further research. On the other hand, our assumption on transaction costs is conservative. Transaction costs in reality might be lower, leading to higher net returns for momentum investors in frontier emerging markets.

2.5. Risk-based explanations

In this section we analyze whether exposure to global risk factors can explain the existence of the factor anomalies and whether the factors are prone to extreme downside risk. We conclude this section with an analysis of the return factors in the recent crisis period.

2.5.1. Exposure to global risk factors

In the previous sections we showed that value and momentum effects, and to a lesser extent the local size effect, are present in frontier emerging markets. However, to which extent do the results serve as out-of-sample evidence of these effects? In this sub-section we address the question of whether our findings are independent of the existence of the effects in emerging and developed markets. In other words, we investigate to which extent the results are driven by well-known global risk factors.

A first analysis to get insight in the independence of our results is by examining the correlations between the strategies across frontier, emerging and developed markets. Miles (2005), Speidell and Krohne (2007), and Berger, Pukthuanthong, and Yang (2011) indicate that investors may benefit from the diversification opportunities of frontier equity market returns. They consider frontier markets as a group at the index level or at the country index level. We want to go one step further in our analysis and examine whether investment strategies in frontier markets correlate with the same strategies in developed and emerging equity markets. If the correlation is low, this might be an indication that value, momentum and size strategies do not have common components across markets.

In order to use international risk factors we need to construct international investment portfolios. The global developed markets size, value, and momentum returns are constructed as follows. Using a survivorship-bias free data set of stock constituents of the FTSE World index, we form monthly rankings according to local size (measured by market capitalization relative to the stocks within their own country), value, and momentum. We form equally-weighted portfolios and calculate US dollar hedged returns using a 12-month holding period. For the emerging markets factor returns we use the same methodology based on all stocks in the S&P/IFCI Emerging Markets index. Returns of these strategies are measured in US dollars.[36]

TABLE 2.5. Correlation between frontier, emerging, and developed market investment strategies

The first row contains the correlations between the equally-weighted market portfolios. The next rows contain the correlations of monthly excess returns of the value, momentum, and size top-minus-index portfolios between frontier markets (FM), emerging markets (EM) and developed markets (DM), for which we respectively use the S&P Frontier BMI, S&P/IFCI Emerging Markets and the FTSE World index. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio. The row denoted by "average" contains the average correlation of the value and momentum strategies. The table contains correlations over the full sample period January 1997 to November 2008 and two sub-samples January 1997 to December 2002 and January 2003 to November 2008.

	Full sample 1997-2008			First half 1997-2002			Second half 2003-2008		
	FM, EM	FM, DM	EM, DM	FM, EM	FM, DM	EM, DM	FM, EM	FM, DM	EM, DM
Market	0.48	0.50	0.82	0.04	0.05	0.75	0.81	0.80	0.91
B/M	0.09	0.06	0.46	0.09	0.05	0.50	0.10	0.10	0.22
E/P	0.01	-0.05	0.27	-0.05	-0.06	0.30	0.16	-0.03	0.17
D/P	0.14	-0.15	0.12	-0.03	-0.19	0.18	0.32	-0.13	-0.03
Average value	0.08	-0.05	0.28	0.00	-0.07	0.33	0.19	-0.02	0.12
MOM3	0.05	0.20	0.32	0.08	0.28	0.23	-0.01	0.10	0.47
MOM6	0.03	0.08	0.26	0.04	0.08	0.22	0.03	0.09	0.45
MOM12	0.07	0.00	0.32	0.06	0.01	0.30	0.08	-0.03	0.46
Average momentum	0.05	0.09	0.30	0.06	0.12	0.25	0.03	0.05	0.46
Size	0.13	0.08	0.20	0.17	0.11	0.17	0.05	0.04	0.24

Table 2.5 contains the correlations of returns for the equally-weighted market index and the value, momentum, and size factors between the frontier, emerging and developed markets. The correlations are estimated over the full sample period 1997-2008 and two sub-sample periods from 1997-2002 and 2003-2008. Based on the first row of Table 2.5, we observe that the correlation between the frontier market index and the emerging and developed market indexes over the entire sample period is moderately positive (0.48 and

[36] Hedging emerging markets currencies for the entire index for our entire sample period is virtually impossible because of a lack of sufficiently liquid instruments for some emerging currencies, especially in the beginning of our sample period.

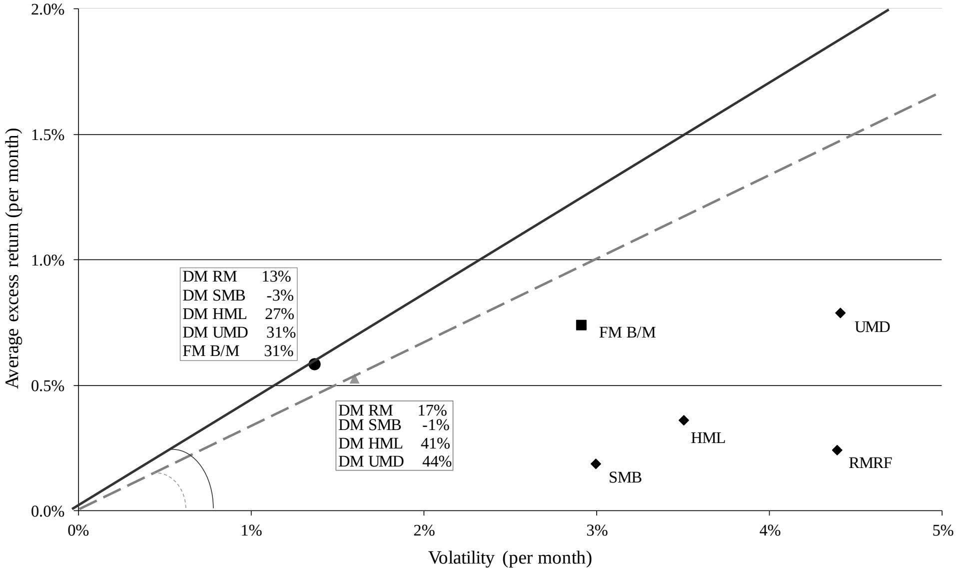
0.50, respectively), confirming the other studies stating that diversification benefits may be obtained from investing in frontier markets. The sub-sample analysis suggests that recently the correlation has increased, although this could be due to the financial crisis in the second half of 2008 in which all risky asset classes were highly correlated.

A different picture emerges when looking at the correlation of Top-Minus-Index investment strategy returns. Strikingly, none of the correlations with the frontier market investment strategies on the full sample exceed 0.2, with the average correlation below 0.10. As an example, the correlation of the 6-month momentum strategy between frontier markets and emerging markets is 0.03 and between frontier and developed markets is 0.08. Furthermore, we do not find higher correlations between frontier and emerging markets than between frontier and developed markets. In the most recent sub-sample, correlations of the value factors between frontier and emerging markets slightly increased, but are still low with an average below 0.2.

These preliminary results indicate that the return factors in frontier markets seem to be independent of the existence of the effects in emerging and developed markets. Additionally, our results support findings of Griffin, Ji, and Martin (2003, 2005), Naranjo and Porter (2007), and Asness, Moskowitz, and Pedersen (2013), who suggest that investors may benefit from combining the same strategies in different (non-frontier) countries, as the returns from these strategies are far from perfectly positively correlated.

We continue by investigating whether the mean-variance efficient frontier of a portfolio invested in developed equity factor portfolios can be expanded by including investment strategies from frontier markets. In an unreported analysis, we find that when the frontier markets index is used as the new asset and emerging and developed markets indexes are used as the two base assets that the mean-variance efficient frontier is significantly expanded. We take our mean-variance spanning analysis one step further by testing whether the frontier market factor returns can expand the mean-variance frontier for investors in the same factors in developed and emerging markets. This is illustrated by Figure 2.2, in which the average return and volatility risk of the four international developed markets Carhart (1997) benchmark assets (market, value, size, and momentum) are displayed, as well as the dashed line that represents the mean-variance frontier based on these assets. The square indicates the B/M strategy in frontier markets. The optimal benchmark portfolio scaled to sum to 100% consists of 17% in the entire market, -1% in the size strategy, 41% in the value strategy and 44% in the momentum strategy. This strategy is shown on the mean-variance frontier with a triangle at a risk of 1.6% per month. In case the B/M strategy based on frontier markets is added to the investment opportunity set, the mean-variance frontier expands with the optimal weight to this new asset class of 31%. This portfolio is also shown on the mean-variance frontier.

FIGURE 2.2. Mean-variance spanning tests for frontier markets value strategy
This figure plots portfolios by their average excess return and volatility risk. The base assets are based on global developed markets and indicated with diamonds: RMRF is the market, SMB the size strategy, HML the value (book-to-market) strategy, and UMD the (6-month) momentum strategy. The dashed line with triangle is on the mean-variance frontier of the four developed markets portfolios. The solid line is the mean-variance frontier with in addition to the four base assets from the developed markets also the Top minus Index B/M value strategy based on frontier markets included (the stand alone frontier markets Top minus Index B/M value strategy is indicated with a square). The portfolio weights from each of these lines are also displayed in the figure, scaled such that the weights equal one.



Whether this portfolio weight of 31% is also significantly different from zero from a statistical point of view can be tested using mean-variance spanning tests; see De Roon and Nijman (2001) for an overview of interpretations of mean-variance spanning tests. They also indicate that tests for differences in Sharpe ratios of these two efficient portfolios, for example using the Jobson and Korkie (1981) test, is closely related to using alphas from regression-based mean-variance spanning tests. Sharpe ratios can be used to determine whether one portfolio is to be preferred over another, whereas alpha answers the question whether investors can improve the efficiency of their portfolio by investing in the new asset. In case the optimal portfolio weight of the new asset would be zero, the mean-variance frontiers would coincide, the alpha would be zero, and the Sharpe ratios of both portfolios would be the same.

A more direct analysis to assess the influence of global components would be to run a multiple regression of the frontier market return factors on their global counterparts. This approach is closely related to a formal mean-variance spanning test; see Huberman and Kandel (1987). For that purpose we estimate the following regression equation:

$$\text{(2.1)}\quad R^{e}_{TMI,t} = \alpha + \beta_{M} R^{e}_{M,t} + \beta_{SMB} R^{e}_{SMB,t} + \beta_{HML} R^{e}_{HML,t} + \beta_{UMD} R^{e}_{UMD,t} + \varepsilon_{t}$$

with SMB the local size factor, HML the value factor measured by the book-to-market ratio, and UMD the 6-month momentum factor. In line with the literature, we use Top minus Bottom portfolio returns for the developed and emerging factors. These are essentially the four factors from Carhart (1997). An alpha statistically different from zero implies that the excess returns in frontier markets cannot be explained by global risk factors and hence these frontier market return factors are independent of existing effects in other markets.

The estimation results of Equation 2.1 are displayed in Table 2.6. Panel A contains the estimates for global developed risk factors and Panel B for global emerging risk factors.[37] The positive alphas reported in Panel A and Panel B are similar to the previously reported excess returns as shown in the first two columns and are statistically significantly different from zero.

For example, the E/P strategy has a statistically significant alpha of 1.23% and 1.26% per month relative to the developed and emerging risk factors, respectively. Corresponding t-values are 5.69 and 5.28, respectively. The excess return of the TMI strategy reported before is 1.26%, as indicated in the first column. For the 6-month momentum strategy the alpha is 0.75% (t-value 4.26) when adjusted for developed markets and 0.76% (t-value 3.73) when adjusted for emerging markets risk factors compared to a TMI excess return of 0.77% per month. We find similar results for the local size factor where the alpha is 0.52% (t-value of 3.03) when adjusted for developed markets and 0.50% (t-value is 2.93) when adjusted for emerging markets risk factors. These results reinforce our earlier results that correlations between return factors in frontier markets, developed and emerging markets are generally low.[38]

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[37] We have also analyzed US-based factors from the online data library of Kenneth French. The results are qualitatively the same, see Appendix 2.C. We also show in Appendix 2.C that our results cannot be explained by the traded liquidity factor of Pastor and Stambaugh (2003) and non-traded liquidity factors of Sadka (2006).

[38] The conclusions do not change when we regress net excess returns of our investment strategies on the same risk factors, see Appendix 2.D.

TABLE 2.6. Regressions of frontier markets excess returns on global risk factors

The table presents coefficient estimates and t-values of the regression equation: $R^e_{TMI,t} = \alpha + \beta_M R^e_{M,t} + \beta_{SMB} R^e_{SMB,t} + \beta_{HML} R^e_{HML,t} + \beta_{UMD} R^e_{UMD,t} + \varepsilon_t$, where $R^e_{TMI,t}$ is the return in month t of the top-minus-index portfolio of a particular strategy, $R^e_{M,t}$ the excess return of the equally-weighted equity markets portfolio in US dollars minus the 1-month US T-bill return in month t. $R^e_{SMB,t}$ (small-minus-big), $R^e_{HML,t}$ (high-minus-low), and $R^e_{UMD,t}$ (up-minus-down) are Top minus Bottom returns on size, book-to-market, and 6-month momentum factor portfolios, respectively. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio. t(.) is the t-value for the regression coefficients and are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). Panel A takes as the set of base assets the four portfolios based on global developed equity markets and Panel B contains results based on base assets from global emerging equity markets.

	TMI	*t(TMI)*	α	$t(\alpha)$	β_M	$t(\beta_M)$	β_{HML}	$t(\beta_{HML})$	β_{SMB}	$t(\beta_{SMB})$	β_{UMD}	$t(\beta_{UMD})$
Panel A: Global developed markets												
B/M	0.74	*3.05*	0.70	*2.87*	-0.04	*-0.73*	-0.02	*-0.15*	0.24	*1.84*	0.02	*0.25*
E/P	1.26	*5.55*	1.23	*5.69*	0.05	*1.23*	-0.10	*-1.48*	0.17	*1.51*	0.04	*0.61*
D/P	0.41	*1.72*	0.56	*2.54*	-0.09	*-2.17*	-0.06	*-0.88*	-0.17	*-1.88*	-0.11	*-2.26*
MOM3	0.95	*6.52*	0.88	*6.18*	-0.01	*-0.15*	-0.01	*-0.36*	0.11	*1.44*	0.09	*2.63*
MOM6	0.77	*4.02*	0.75	*4.26*	0.01	*0.21*	-0.05	*-0.82*	0.11	*1.31*	0.03	*0.59*
MOM12	0.59	*3.08*	0.57	*2.80*	0.04	*0.73*	0.05	*0.87*	-0.04	*-0.44*	-0.01	*-0.20*
Size	0.47	*2.58*	0.52	*3.03*	-0.05	*-1.18*	0.05	*0.96*	-0.06	*-0.74*	-0.09	*-1.96*
Panel B: Global emerging markets												
B/M	0.74	*3.05*	0.73	*2.73*	-0.01	*-0.27*	0.02	*0.33*	0.08	*0.83*	-0.03	*-0.54*
E/P	1.26	*5.55*	1.26	*5.28*	0.04	*1.46*	-0.03	*-0.82*	0.11	*1.52*	0.00	*0.00*
D/P	0.41	*1.72*	0.46	*2.06*	-0.07	*-2.78*	0.02	*0.54*	-0.11	*-1.79*	-0.02	*-0.59*
MOM3	0.95	*6.52*	0.92	*6.00*	-0.02	*-0.75*	0.02	*0.67*	0.02	*0.44*	0.02	*0.68*
MOM6	0.77	*4.02*	0.76	*3.73*	0.00	*-0.11*	0.01	*0.29*	0.00	*-0.01*	0.01	*0.35*
MOM12	0.59	*3.08*	0.61	*3.18*	0.02	*0.48*	0.00	*-0.04*	-0.09	*-1.22*	-0.01	*-0.20*
Size	0.47	*2.58*	0.50	*2.93*	0.00	*0.06*	-0.03	*-0.77*	0.09	*1.22*	-0.03	*-1.02*

Our analysis in Table 2.6 suggests that global risk factors cannot explain the excess returns in frontier markets. Our results are in line with the findings by Van der Hart, De Zwart, and Van Dijk (2005), who claim that value and momentum investment strategies in emerging markets are not exposed to global risk factors. Of course, our results do not rule out that local risk factors can explain these effects. Unfortunately, limited data availability in these markets (for example on earnings or earnings estimates) does not allow us to disentangle local risk factors from behavioral explanations. We think this is a fruitful area for further research once more reliable data becomes available.

2.5.2. Downside risk

Although the descriptive statistics in Table 2.1 show that the volatility of the aggregated frontier markets is not high, the factor returns might have more extreme observations in the sense of higher skewness and kurtosis than can be expected based on normality. Therefore, we calculate in addition to the average and standard deviation of portfolio returns also the skewness and kurtosis.[39] We display these results in Table 2.7. The positive values show that excess kurtosis often exceeds the prediction derived from normally distributed returns. This indicates that there are more extreme returns than mean and variance can capture. Interestingly, the skewness for most of the factor returns (apart from 6-month momentum) is also positive, indicating that the deviation from normality is due to exceptionally large upward potential instead of increased downside risk.

In order to examine downside risk in more detail, we compare empirical estimates of downside risk to the theoretical equivalent under the assumption of normality. More precisely, we calculate the 1% and 2.5% and 97.5% and 99% percentiles of the monthly returns and compare these to the parametric percentile derived from the normal distribution with the same mean and variance as our strategies. These results confirm our prediction based on the positive skewness and kurtosis, in the sense that it is the upward potential instead of the downside risk that causes deviations from normality. Based on the 1% percentile, we find that most strategies exhibit comparable or lower downside risk than would be expected based on a normal distribution. Only the 12-month momentum strategy exhibits substantially higher downside risk, as the empirical 1% percentile is -5.19% versus -4.67% based on the 1% theoretical percentile. Based on the 2.5% percentile we find that all

[39] We also computed the Jarque-Bera test on the normality of portfolio returns. This test is based on the skewness and kurtosis. We frequently reject normality, but this is not so much due to increased downside risk, but due to higher upside. This is why we empirically determine the downside risk of our strategies and compare these to the risk measures following from a normal distribution.

strategies exhibit a lower downside risk than expected based on a normal distribution. Additionally, we find that many factor returns exhibit empirically higher upside potential that would be expected based on a normal distribution. For example, the B/M strategy's 99% percentile is 10.12%, whereas based on the normal distribution this would be 7.52%. In case the upside is less, the differences are small with the expected upside. Hence, we deem it unlikely that downside risk can explain the empirical results we document.

TABLE 2.7. Downside risk
The first four rows display average, volatility, skewness and excess kurtosis of the monthly top-minus-index excess returns of frontier markets portfolios. The following rows compare the parametric percentile derived from the normal distribution to empirical estimates of tail risk calculated as 1%, 2.5%, 97.5% and 99% percentiles of the monthly excess returns. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio.

	B/M	E/P	D/P	MOM3	MOM6	MOM12	Size
Average	0.74%	1.26%	0.41%	0.95%	0.77%	0.59%	0.47%
Volatility	2.92%	2.35%	2.36%	1.59%	2.15%	2.26%	2.08%
Skewness	0.80	0.54	-0.07	0.61	-2.03	1.23	0.25
Kurtosis	2.52	0.44	1.98	0.68	15.58	6.85	0.72
Theoretical 1%	-6.05%	-4.22%	-5.09%	-2.75%	-4.22%	-4.67%	-4.38%
Empirical 1%	-6.12%	-2.99%	-5.13%	-2.48%	-2.92%	-5.19%	-4.19%
Theoretical 2.5%	-4.98%	-3.35%	-4.22%	-2.17%	-3.44%	-3.84%	-3.61%
Empirical 2.5%	-4.68%	-2.65%	-3.46%	-1.50%	-2.30%	-2.90%	-3.60%
Theoretical 97.5%	6.45%	5.87%	5.04%	4.07%	4.97%	5.02%	4.55%
Empirical 97.5%	7.00%	6.51%	4.80%	4.79%	4.75%	4.82%	4.73%
Theoretical 99%	7.52%	6.73%	5.91%	4.65%	5.76%	5.85%	5.31%
Empirical 99%	10.12%	7.23%	5.62%	5.23%	5.71%	6.44%	6.27%

2.5.3. Results for the crisis period 2008-2011

The turmoil in financial markets after our research period 1997 to 2008 is an interesting out-of-sample period to test whether the return factors we document are still present in our sample of frontier emerging markets. For the recent crisis period ranging from December 2008 to December 2011 (37 months), we make use of the frontier market data sources to form portfolios in exactly the same fashion as done in our previous analyses.[40] In November 2008, the S&P Frontier BMI experienced major changes and has expanded from 24 to 35 countries, including the five Gulf Cooperative Council (GCC) country members. As our data provider is not able to cope with these GCC countries, because the trading days also include

[40] We verify that the data is of high quality by calculating the index return from individual stock returns and market capitalisations and comparing the index return with the return published by S&P on the index.

(Western) weekends, we focus in this sub-section on the main analyses conducted on the dataset excluding these countries and use our original dataset for all further analyses.

The out-of-sample results are presented in Table 2.8. Panel A shows the excess returns of the return factors over this period. We see that value and size effects have been strong over the past 37 months in the recent crisis period. Similar to developed and emerging markets, momentum effects have not been present in this period filled with turmoil. This is due to the market reversal, from down in 2008 to up in 2009 and down again in 2011. As indicated by Blitz, Huij, and Martens (2011), momentum strategies exhibit time-varying risk factors and hence are likely to underperform in markets with strong reversals. Note that the returns of the momentum strategies in frontier markets are still economically and statistically significant over the whole sample period from 1997 until 2011. Our results once more indicate that value and momentum show different return patterns implying that combining both types of strategies leads to diversification benefits.

In Panel B of Table 2.8, we display the correlation between the factor returns in developed, emerging, and frontier markets for the out-of-sample period. We see that the correlation between developed and emerging markets has remained high at 0.90 at the market level, while frontier markets' correlation with emerging and developed markets has increased to 0.76 and 0.78. For most other factors, the correlation of frontier markets with developed and emerging markets has increased to around 0.5. This indicates that the diversification benefits that we observed in our sample have become smaller in the out-of-sample period. Nevertheless, the correlation with frontier markets factors remains substantially below the correlation between developed and emerging markets, indicating that investors could still reap diversification benefits by investing in the frontier market factors, although less than before.

2.6. Conclusions

The new emerging equity markets, the so-called frontier emerging markets, are attracting increased attention from foreign investors. Research on these frontier markets is scarce and mostly conducted using the frontier market as a whole or at the country level. In this study, we dig one step deeper and analyze the cross-section of individual stock returns. Our research on individual stocks in frontier emerging markets makes use of a unique high-quality and survivorship-bias free dataset. The use of individual stock characteristics data allows us to investigate the added value of investment strategies relative to strategies that only use aggregated data at the country level. We use data from more than 1,400 stocks from 24 frontier markets over a 12-year period from 1997 to 2008. This previously untapped data

TABLE 2.8. Results for the crisis period December 2008 to December 2011

Panel A presents excess returns of portfolios sorted on value, momentum and size characteristics and is similar to Table 2.2, but now for the 37 months out-of-sample period. Panel B presents the correlation of frontier markets portfolios with developed and emerging markets where the full sample results are similar to Table 2.5.

	B/M		E/P		D/P		MOM3		MOM6		MOM12		Size	
	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*	Return	*t-value*
Panel A. Excess returns of portfolios sorted on characteristics														
Top-Minus-Index	0.68	*1.08*	0.98	*2.30*	0.66	*2.14*	-0.08	*-0.24*	-0.38	*-0.72*	-0.56	*-0.86*	1.40	*2.70*
Top-Minus-Bottom	1.52	*1.24*	1.88	*2.31*	1.66	*4.30*	-0.49	*-0.55*	-1.12	*-0.85*	-1.20	*-0.75*	2.64	*2.94*
Index-Minus-Bottom	-0.84	*-1.24*	-0.90	*-1.86*	-1.01	*-3.70*	0.41	*0.61*	0.75	*0.85*	0.64	*0.63*	-1.25	*-2.45*
EW Market risk adjusted	0.69	*1.14*	0.99	*2.27*	0.66	*2.37*	-0.08	*-0.30*	-0.38	*-0.93*	-0.57	*-1.29*	1.40	*3.04*
VW Market risk adjusted	0.78	*1.31*	1.04	*2.37*	0.69	*2.14*	-0.23	*-0.75*	-0.62	*-1.26*	-0.91	*-1.64*	1.39	*2.64*

	Full sample 1997-2008			Crisis period 2008-2011		
	FM, EM	FM, DM	EM, DM	FM, EM	FM, DM	EM, DM
Panel B. Correlation of frontier markets portfolios with developed and emerging markets						
Market	0.48	0.50	0.82	0.76	0.78	0.90
B/M	0.09	0.06	0.46	0.57	0.48	0.79
E/P	0.01	-0.05	0.27	0.63	0.63	0.88
D/P	0.14	-0.15	0.12	0.36	-0.34	-0.15
Average value	0.08	-0.05	0.28	0.52	0.26	0.51
MOM3	0.05	0.20	0.32	0.33	0.36	0.83
MOM6	0.03	0.08	0.26	0.67	0.64	0.88
MOM12	0.07	0.00	0.32	0.72	0.68	0.83
Average momentum	0.05	0.09	0.30	0.57	0.56	0.85
Size	0.13	0.08	0.20	0.43	0.43	0.77

source provides excellent opportunities for out-of-sample research related to investment strategies that were previously analyzed in developed and emerging markets.

Our empirical results indicate that portfolios based on value and momentum in frontier markets generate economically and statistically significant excess returns of about 5 to 15% per annum. The magnitude of these excess returns is at least as large as those found before in developed and emerging markets. We also find that there is a local size effect in frontier markets. These are striking empirical observations, as integration of frontier markets with developed and emerging markets is generally low. Our results are valuable out-of-sample evidence of the cross-section of stock returns previously documented in developed markets. These results are robust as they still hold after performing a battery of robustness analyses, such as an analysis by geographical region and financial liberalization.

Investors who are interested to capture the value and momentum effect might be concerned with the transaction costs involved, as liquidity is typically lower than for more developed equity markets. We analyze the after transaction costs returns of value and momentum strategies using conservative estimates from Marshall et al. (2013) on a liquid sample of the largest 150 frontier market stocks including a one-month skip between ranking and implementation of the stocks in portfolio. Our results indicate that net excess returns are approximately 7% per annum for value and momentum strategies. These excess returns are both economically and statistically significant and therefore do not explain the existence of these factor returns.

We additionally investigate whether the factor returns in frontier markets can be explained by risk. First, our results are not driven by frontier market, country- or region exposures, as our results still hold when correcting for these exposures. Second, our results cannot be explained by exposure to global risk factors, such as market, value, momentum and size. Third, it is unlikely that downside risk can explain the empirical results. Hence, we believe it is unlikely that transaction costs or risk can explain the strong factor returns. Although we cannot rule out that exposures to other global risk factors or local risk might explain the returns of the strategies, future research could investigate to which extent behavioral biases might explain the value, momentum and size effect in frontier markets.

2.A. Globalization scores for frontier market countries over time

TABLE 2.A.1. Globalization scores for frontier market countries over time

Panel A is based on the Index of Economic Freedom reported by The Heritage Foundation (HF), available at http://www.heritage.org. We report the average of the sub-indices Financial Freedom and Investment Freedom. Panel B is based on the KOF Index of Globalization constructed by the ETH Zurich (KOF), available at http://globalization.kof.ethz.ch. We report the Economic Globalization dimension scores. Panel C is based on the Economic Freedom of the World reported by Fraser Institute (EFW), available at http://www.freetheworld.com. The table reports the scores of the area Freedom to Trade Internationally. The column headers in the panels refer to the year the data have become available. We assume HF and KOF data have become available at the end of March every year, while EFW data have become available at the end of September every year. The last three rows show the average scores of frontier markets (FM), emerging markets (EM) based on stocks included in the S&P/IFCI Emerging Markets index and developed markets (DM) based on stocks in the FTSE World index.

Country	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Panel A. HF scores													
Bangladesh	50	50	50	40	40	40	40	40	40	20	30	25	20
Botswana	60	60	60	60	60	60	70	70	70	70	70	70	70
Bulgaria	60	50	50	60	60	60	60	50	60	60	70	60	60
Côte d'Ivoire	50	50	50	50	50	50	60	60	60	60	60	55	50
Croatia		50	50	50	50	50	50	50	60	60	60	55	55
Ecuador	60	60	60	60	60	50	50	50	50	40	40	45	45
Estonia		80	80	80	80	80	90	90	90	90	90	90	85
Ghana	50	50	50	50	50	50	50	50	50	40	50	50	50
Jamaica	70	70	70	60	60	50	60	80	80	80	80	70	70
Kazakhstan												45	45
Kenya	50	60	60	60	60	50	50	50	50	50	50	50	50
Latvia		70	70	70	70	70	70	70	70	70	70	70	70
Lebanon				60	60	60	60	60	60	50	50	50	50
Lithuania	40	60	60	60	60	60	60	70	80	80	80	75	75
Mauritius	-	-	-	60	60	60	60	60	60	60	60	65	65
Namibia				70	70	60	60	70	50	50	50	50	40
Panama												65	70
Romania		60	60	60	60	40	40	50	40	40	50	55	55
Slovakia									80	80	80	75	75
Slovenia	50	60	70	70	50	50	50	50	50	50	60	60	55
Trinidad and Tobago	80	80	80	80	80	80	70	70	70	70	70	70	70
Tunisia	70	70	70	60	60	60	60	50	50	30	30	30	30
Ukraine		40	40	40	40	40	40	40	40	40	40	40	40
Vietnam											30	30	30
average FM score	58	60	61	60	59	56	58	59	60	57	58	56	55
average EM score	58	58	60	59	57	55	57	54	53	51	50	50	52
average DM score	69	70	68	69	69	71	73	73	73	73	72	72	75

TABLE 2.A.1. Globalization scores for frontier market countries over time (continued)

Country	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Panel B. KOF scores													
Bangladesh	11	11	11	15	16	18	21	24	25	26	28	32	33
Botswana	52	54	59	61	64	64	64	67	73	76	74	72	65
Bulgaria	43	46	47	53	59	58	61	66	65	62	67	74	72
Côte d'Ivoire	31	34	34	34	36	39	41	45	44	45	45	45	48
Croatia		50	46	51	55	56	60	59	60	63	67	73	75
Ecuador	41	44	51	52	52	54	59	61	59	57	56	55	54
Estonia		76	76	78	87	86	87	89	90	89	91	93	92
Ghana	30	33	30	36	32	37	38	41	40	42	50	56	50
Jamaica	66	68	69	68	67	68	70	71	70	70	69	73	73
Kazakhstan												72	73
Kenya	40	38	37	32	33	32	32	33	32	34	39	37	37
Latvia		58	60	67	70	71	71	70	71	73	74	80	81
Lebanon				-	-	-	-	-	-	-	-	-	-
Lithuania	54	55	57	63	67	70	69	69	73	75	73	78	79
Mauritius	42	39	44	46	47	46	48	53	48	46	44	39	55
Namibia				56	55	56	50	55	54	60	57	59	59
Panama												79	78
Romania		34	36	41	46	50	51	54	54	54	56	65	69
Slovakia									78	72	68	89	87
Slovenia	52	52	52	56	59	59	59	63	66	69	73	79	79
Trinidad and Tobago	66	69	73	73	73	73	71	72	76	74	74	72	75
Tunisia	50	51	49	49	52	54	52	55	54	58	56	58	64
Ukraine		37	42	44	45	49	53	55	52	53	53	56	61
Vietnam											47	50	53
average FM score	44	47	49	51	53	55	56	58	59	60	60	65	66
average EM score	54	54	57	58	59	60	60	61	64	66	66	67	66
average DM score	72	74	74	75	77	80	81	84	81	80	80	79	79

TABLE 2.A.1. Globalization scores for frontier market countries over time (continued)

Country	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Panel C. EFW scores													
Bangladesh	1.8	3.1	3.1	3.1	3.1	3.1	5.1	5.4	5.6	5.4	5.4	5.5	5.9
Botswana	7.3	6.8	6.8	6.8	6.8	6.8	7.8	7.7	7.6	7.3	7.1	6.8	6.9
Bulgaria	4.3	6.9	6.9	6.9	6.9	6.9	7.2	7.1	6.7	7.2	7.3	7.2	7.7
Côte d'Ivoire	5.2	5.8	5.8	5.8	5.8	5.8	6.0	6.0	6.1	6.1	6.0	5.8	6.0
Croatia		6.0	6.0	6.0	6.0	6.0	6.2	6.5	6.4	6.6	6.7	6.5	6.7
Ecuador	5.8	6.7	6.7	6.7	6.7	6.7	7.1	7.0	6.5	6.5	6.6	6.7	6.6
Estonia		8.6	8.6	8.6	8.6	8.6	8.8	8.8	8.5	8.4	8.4	8.1	8.1
Ghana	5.0	5.8	5.8	5.8	5.8	5.8	7.2	7.3	6.9	7.2	7.1	5.6	7.0
Jamaica	5.4	7.5	7.5	7.5	7.5	7.5	7.2	7.2	7.0	6.7	6.9	6.9	7.0
Kazakhstan												7.1	6.9
Kenya	5.2	7.6	7.6	7.6	7.6	7.6	7.1	6.9	6.5	6.7	6.5	6.3	6.6
Latvia		8.0	8.0	8.0	8.0	8.0	7.2	7.6	7.4	7.5	7.4	7.4	7.4
Lebanon				-	-	-	-	-	-	-	-	-	-
Lithuania	-	8.2	8.2	8.2	8.2	8.2	7.3	7.8	7.7	7.6	7.5	7.5	7.5
Mauritius	5.6	7.2	7.2	7.2	7.2	7.2	6.8	7.0	6.5	6.3	6.1	7.2	7.4
Namibia				6.4	6.4	6.4	6.2	6.7	6.5	6.5	6.4	6.3	6.4
Panama												7.9	8.3
Romania		5.9	5.9	5.9	5.9	5.9	6.4	6.5	6.6	6.7	6.9	7.1	7.1
Slovakia									8.2	8.3	8.8	8.1	8.2
Slovenia	-	7.1	7.1	7.1	7.1	7.1	7.1	7.2	7.0	7.2	7.4	7.2	7.2
Trinidad and Tobago	3.9	7.3	7.3	7.3	7.3	7.3	6.7	7.2	6.9	6.9	7.1	6.9	7.1
Tunisia	6.0	6.2	6.2	6.2	6.2	6.2	6.0	6.4	6.0	6.0	6.2	6.0	6.2
Ukraine		6.2	6.2	6.2	6.2	6.2	7.0	6.8	7.1	6.9	7.0	6.5	6.4
Vietnam										6.8	6.7	6.6	6.9
average FM score	5.0	6.7	6.7	6.7	6.7	6.7	6.9	7.0	6.9	6.9	6.9	6.8	7.0
average EM score	5.9	5.9	5.8	5.8	5.8	5.8	6.7	7.1	7.2	7.1	7.1	7.2	7.1
average DM score	7.7	7.7	7.7	7.6	7.6	7.6	7.9	8.3	8.2	7.9	7.9	7.8	7.4

2.B. Individualism scores for frontier countries

TABLE 2.B.1. Individualism scores for frontier countries

Data on individualism obtained from www.geert-hofstede.com. The scores are displayed for the frontier countries for which the data is available. The group with low-individualism scores are all countries, except for Estonia, Jamaica, Lebanon, and Slovakia (in black), who have a score above the threshold of 32 that is the cut-off point of the bottom individualism group in Chui, Titman, and Wei (2010).

Country	Score	Country	Score
Bangladesh	20	Lebanon	38
Botswana	-	Lithuania	-
Bulgaria	30	Mauritius	-
Côte d'Ivoire	-	Namibia	-
Croatia	-	Panama	11
Ecuador	8	Romania	30
Estonia	60	Slovakia	52
Ghana	20	Slovenia	-
Jamaica	39	Trinidad & Tobago	16
Kazakhstan	-	Tunisia	-
Kenya	27	Ukraine	-
Latvia	-	Vietnam	20
Average frontier markets below treshhold 32			20
Average bottom individualism Chui et al (2010)			22
World average as reported by Hofstede (2001)			43

2.C. Regressions of frontier markets excess returns on US risk factors

TABLE 2.C.1. Regressions of frontier markets excess returns on US risk factors

Panel A of the table presents coefficient estimates and t-values of the regression equation: $R^e_{TMI,t} = \alpha + \beta_M R^e_{M,t} + \beta_{SMB} R^e_{SMB,t} + \beta_{HML} R^e_{HML,t} + \beta_{UMD} R^e_{UMD,t} + \varepsilon_t$, where $R^e_{TMI,t}$ is the return in month t of the top-minus-index portfolio of a particular strategy, $R^e_{M,t}$ the excess return of the equally-weighted equity markets portfolio in US dollars minus the 1-month US T-bill return in month t. $R^e_{SMB,t}$ (small-minus-big), $R^e_{HML,t}$ (high-minus-low), and $R^e_{UMD,t}$ (up-minus-down) are Top minus Bottom returns on size, book-to-market, and 6-month momentum factor portfolios, respectively. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio. Data on the US-based portfolios are from the online data library of Kenneth French. t(.) is the t-value for the regression coefficients and are corrected for heteroskedasticity and autocorrelation using Newey and West (1987). In Panel B we add as a fifth factor the traded liquidity factor (LIQ PS), obtained from the website of Luboš Pástor. Details on the liquidity factor can be found in Pastor and Stambaugh (2003). In Panel C, we add the non-traded fixed-transitory (LIQ S-FT) and variable-permanent (LIQ S-VP) liquidity factors, obtained from Ronnie Sadka and described in more detail in Sadka (2006).

	TMI	t(TMI)	α	t(α)	β_M	t(β_M)	β_{SMB}	t(β_{SMB})	β_{HML}	t(β_{HML})	β_{UMD}	t(β_{UMD})	$\beta_{LIQ\,PS}$	t($\beta_{LIQ\,PS}$)	$\beta_{LIQ\,S\text{-}FT}$	t($\beta_{LIQ\,S\text{-}FT}$)	$\beta_{LIQ\,S\text{-}VP}$	t($\beta_{LIQ\,S\text{-}VP}$)
Panel A. US; Market, Size, Value, and Momentum																		
B/M	0.74	*3.05*	0.72	*2.93*	-0.06	*-1.11*	0.09	*1.24*	0.11	*1.40*	-0.05	*-1.21*						
E/P	1.26	*5.55*	1.28	*5.84*	0.02	*0.35*	0.00	*0.08*	0.07	*1.36*	-0.04	*-1.56*						
D/P	0.41	*1.72*	0.47	*2.12*	-0.06	*-1.56*	-0.11	*-1.94*	-0.03	*-0.78*	0.00	*-0.14*						
MOM3	0.95	*6.52*	0.93	*6.46*	-0.02	*-0.45*	0.01	*0.11*	0.04	*1.05*	0.02	*0.67*						
MOM6	0.77	*4.02*	0.78	*4.24*	0.00	*-0.08*	-0.05	*-0.94*	0.03	*0.70*	0.00	*-0.03*						
MOM12	0.59	*3.08*	0.62	*3.11*	0.00	*0.04*	-0.05	*-0.90*	-0.01	*-0.23*	-0.01	*-0.17*						
Size	0.47	*2.58*	0.59	*3.57*	-0.05	*-1.38*	-0.04	*-0.71*	-0.04	*-0.76*	-0.10	*-4.38*						
Panel B. US; Market, Size, Value, Momentum, and Liquidity (PS)																		
B/M	0.74	*3.05*	0.68	*2.72*	-0.08	*-1.15*	0.08	*1.01*	0.11	*1.36*	-0.05	*-1.28*	0.05	*0.55*				
E/P	1.26	*5.55*	1.26	*5.51*	0.00	*0.08*	-0.01	*-0.09*	0.07	*1.33*	-0.05	*-1.60*	0.03	*0.47*				
D/P	0.41	*1.72*	0.49	*2.05*	-0.05	*-1.09*	-0.10	*-1.57*	-0.02	*-0.71*	0.00	*-0.13*	-0.02	*-0.30*				
MOM3	0.95	*6.52*	0.93	*5.92*	-0.02	*-0.44*	0.01	*0.12*	0.04	*1.05*	0.02	*0.67*	0.00	*-0.05*				
MOM6	0.77	*4.02*	0.84	*4.60*	0.02	*0.40*	-0.02	*-0.48*	0.04	*0.88*	0.00	*0.04*	-0.08	*-1.40*				
MOM12	0.59	*3.08*	0.66	*3.28*	0.02	*0.45*	-0.03	*-0.52*	0.00	*-0.09*	-0.01	*-0.16*	-0.06	*-1.09*				
Size	0.47	*2.58*	0.63	*3.61*	-0.04	*-0.73*	-0.03	*-0.39*	-0.03	*-0.60*	-0.10	*-4.38*	-0.05	*-0.73*				
Panel C. US; Market, Size, Value, Momentum, and Liquidity (Sadka)																		
B/M	0.74	*3.05*	0.73	*2.96*	-0.08	*-1.26*	0.04	*0.50*	0.09	*1.16*	-0.06	*-1.57*			*0.03*	2.32	*0.00*	0.79
E/P	1.26	*5.55*	1.31	*6.36*	-0.02	*-0.43*	-0.06	*-1.19*	0.06	*1.05*	-0.07	*-2.50*			*0.02*	1.06	*0.01*	3.02
D/P	0.41	*1.72*	0.46	*2.02*	-0.04	*-1.16*	-0.09	*-1.29*	-0.02	*-0.60*	0.01	*0.21*			*0.00*	-0.23	*0.00*	-1.05
MOM3	0.95	*6.52*	0.91	*6.64*	-0.02	*-0.41*	0.00	*-0.09*	0.03	*0.86*	0.02	*0.82*			*0.01*	0.82	*0.00*	-0.88
MOM6	0.77	*4.02*	0.77	*4.13*	0.01	*0.12*	-0.04	*-0.82*	0.03	*0.69*	0.01	*0.32*			*0.00*	0.55	*0.00*	-0.89
MOM12	0.59	*3.08*	0.62	*3.14*	0.01	*0.24*	-0.02	*-0.25*	0.00	*0.06*	0.00	*0.01*			*-0.02*	-1.18	*0.00*	-0.20
Size	0.47	*2.58*	0.58	*3.45*	-0.05	*-1.22*	-0.06	*-1.04*	-0.05	*-0.96*	-0.09	*-3.93*			*0.02*	1.94	*0.00*	-1.06

2.D. Regressions of frontier markets net excess returns on global risk factors

TABLE 2.D.1. Regressions of frontier markets net excess returns on global risk factors

The table presents coefficient estimates and t-values of the regression equation: $R^e_{TMI,t} = \alpha + \beta_M R^e_{M,t} + \beta_{SMB} R^e_{SMB,t} + \beta_{HML} R^e_{HML,t} + \beta_{UMD} R^e_{UMD,t} + \varepsilon_t$, where $R^e_{TMI,t}$ is the return in month t of the top-minus-index portfolio of a particular strategy, $R^e_{M,t}$ the excess return of the equally-weighted equity markets portfolio in US dollars minus the 1-month US T-bill return in month t. $R^e_{SMB,t}$ (small-minus-big), $R^e_{HML,t}$ (high-minus-low), and $R^e_{UMD,t}$ (up-minus-down) are Top minus Bottom returns on size, book-to-market, and 6-month momentum factor portfolios, respectively. All portfolios are formed as described in Table 2.2. Country neutrality is only applied to the size portfolio. t(.) is the t-value for the regression coefficients and are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). Panel A takes as the set of base assets the four portfolios based on global developed equity markets and Panel B contains results based on base assets from global emerging equity markets.

	TMI	*t(TMI)*	α	*t*(α)	β_M	$t(\beta_M)$	β_{SMB}	$t(\beta_{SMB})$	β_{HML}	$t(\beta_{HML})$	β_{UMD}	$t(\beta_{UMD})$
Panel A. Global developed markets												
B/M	0.56	*2.77*	0.49	*2.37*	0.02	*0.42*	-0.08	*-0.91*	0.25	*2.04*	0.08	*1.25*
E/P	0.64	*2.73*	0.57	*2.39*	0.06	*1.15*	-0.10	*-1.27*	0.17	*1.42*	0.11	*1.57*
D/P	0.64	*2.99*	0.79	*4.00*	-0.09	*-2.34*	-0.13	*-2.37*	-0.05	*-0.56*	-0.10	*-2.21*
MOM3	0.60	*3.99*	0.54	*3.93*	-0.02	*-0.64*	-0.07	*-1.44*	0.16	*2.23*	0.10	*2.76*
MOM6	0.39	*1.95*	0.39	*2.13*	-0.03	*-0.62*	-0.10	*-1.50*	0.20	*2.27*	0.01	*0.24*
MOM12	0.16	*0.80*	0.11	*0.57*	0.01	*0.19*	0.07	*0.98*	0.01	*0.05*	0.02	*0.44*
Panel B. Global emerging markets												
B/M	0.56	*2.77*	0.59	*2.77*	0.01	*0.18*	-0.02	*-0.44*	-0.01	*-0.15*	-0.02	*-0.55*
E/P	0.64	*2.73*	0.56	*2.17*	0.00	*-0.12*	0.07	*1.68*	-0.08	*-1.05*	0.02	*0.56*
D/P	0.64	*2.99*	0.69	*3.45*	-0.08	*-3.14*	0.02	*0.66*	-0.09	*-1.37*	-0.04	*-1.53*
MOM3	0.60	*3.99*	0.58	*3.75*	-0.03	*-1.06*	0.01	*0.17*	0.08	*2.03*	0.01	*0.53*
MOM6	0.39	*1.95*	0.43	*2.18*	-0.02	*-0.53*	-0.04	*-1.17*	0.09	*1.61*	-0.02	*-1.15*
MOM12	0.16	*0.80*	0.20	*1.10*	0.02	*0.46*	-0.04	*-0.79*	0.07	*1.23*	-0.02	*-0.67*

3. Another look at trading costs and short-term reversal profits[41]

Several studies report that abnormal returns associated with short-term reversal investment strategies diminish once trading costs are taken into account. We show that the impact of trading costs on the strategies' profitability can largely be attributed to excessively trading in small-cap stocks. Limiting the stock universe to large-cap stocks significantly reduces trading costs. Applying a more sophisticated portfolio construction algorithm to lower turnover reduces trading costs even further. Our finding that reversal strategies generate 30 to 50 basis points per week net of trading costs poses a serious challenge to standard rational asset pricing models. Our findings also have important implications for the understanding and practical implementation of reversal strategies.

3.1. Introduction

A growing body of literature argues that the short-term reversal anomaly (i.e., the phenomenon that stocks with relatively low (high) returns over the past month or week earn positive (negative) abnormal returns in the following month or week) documented by Rosenberg, Reid and Lanstein (1985), Jegadeesh (1990), and Lehmann (1990) can be attributed to trading frictions in securities markets that weaken the arbitrage mechanism. Kaul and Nimalendran (1990), Ball, Kothari and Wasley (1995) and Conrad, Gultekin and Kaul (1997) report that most of short-term reversal profits fall within bid-ask bounds. And more recently, Avramov, Chordia and Goyal (2006) evaluate the profitability of reversal investment strategies net of trading costs using the model of Keim and Madhavan (1997). They find that reversal strategies require frequent trading in disproportionately high-cost securities such that trading costs prevent profitable strategy execution. Based on these results one might conclude that the abnormal returns associated with reversal investment strategies that are documented in earlier studies create an illusion of profitable investment strategies when, in fact, none exist. The seemingly lack of profitability of reversal investment strategies is consistent with market efficiency.

In this study we show that this argument is not necessarily true. We argue that the reported impact of trading costs on reversal profits can largely be attributed to excessively trading in small-cap stocks. When stocks are ranked on past returns, stocks with the highest volatility have the greatest probability to end up in the extreme quantiles. These stocks are

[41] This chapter is published as De Groot, W., Huij, J. and Zhou, W., 2012, Another look at trading costs and short-term reversal profits, *Journal of Banking and Finance,* 36, 371-382.

typically the stocks with the smallest market capitalizations. Therefore a portfolio that is long-short in the extreme quantiles is typically invested in the smallest stocks. However, these stocks are also the most expensive to trade and reversal profits may be fully diminished by the disproportionally higher trading costs.

At the same time, the turnover of standard reversal strategies is excessively high. Reversal portfolios are typically constructed by taking a long position in loser stocks and short position in winner stocks based on past returns. Then, at a pre-specified interval the portfolios are rebalanced and stocks that are no longer losers are sold and replaced by newly bottom-ranked stocks. Vice versa, stocks that are no longer winners are bought back and replaced by newly top-ranked stocks. While this approach is standard in the stream of literature on empirical asset pricing to investigate stock market anomalies, it is suboptimal when the profitability of an investment strategy is evaluated and trading costs are incorporated.

To investigate the impact of small-cap stocks and rebalancing rules on the profitability of reversal strategies, we design and test three hypotheses: first, we gauge the profitability of reversal strategies applied to various market cap segments of the U.S. stock market. Our hypothesis is that the reported impact of trading costs on reversal profits can largely be attributed to excessively trading in small-cap stocks and that limiting the stock universe to large-cap stocks significantly reduces trading costs. Our second hypothesis is that trading costs can be reduced even further without giving up too much of the gross reversal profits when a slightly more sophisticated portfolio construction algorithm is applied. Third, we extend our analyses of reversal profits within different segments of the U.S. market with an analysis across different markets and evaluate the profitability of reversal strategies in European stocks markets. Our hypothesis is that trading costs have a larger impact on reversal profits in European markets since these markets are less liquid. For robustness, we also evaluate reversal profits across various market cap segments of the European stock markets.

Throughout our study we use trading cost estimates resulting from the Keim and Madhavan (1997) model and estimates that were provided to us by Nomura Securities, one of world’s largest stock brokers. Consistent with Avramov, Chordia and Goyal (2006) we find that the profits of a standard reversal strategy are smaller than the likely trading costs for a broad universe that includes small-cap stocks. At the same time we find that the impact of trading costs on short-term reversal profits becomes substantially lower once we exclude small-cap stocks that are the most expensive to trade. In fact, when we focus on the largest U.S. stocks we document significant reversal profits up to 30 basis points per week.

When we also apply a slightly more sophisticated portfolio construction algorithm and do not directly sell (buy back) stocks that are no longer losers (winners) but wait until these stocks are ranked among the top (bottom) 50 percent of stocks based on past returns, the turnover and trading costs of the strategy more than halve and we find even larger reversal profits up to 50 basis points per week. This number is highly significant from both a statistical and an economical point of view.

Additionally, we find that trading costs have a larger impact on reversal profits in European markets. While standard reversal strategies based on a broad universe of European stocks yield gross returns of 50 basis points per week, their returns net of trading costs are highly negative. Once we exclusively focus on the largest stocks and apply the "smart" portfolio construction rules, we document significantly positive net reversal profits up to 20 basis points per week.

In addition, we look at various other aspects of the reversal strategy to evaluate if the strategy can be applied in practice. Amongst others, we document that the reversal effect can be exploited by a sizable strategy with a trade size of one million USD per stock; and that the strategy also earned large positive net returns over the post-decimalization era of U.S. stock markets.

We deem that our study contributes to the existing literature in at least two important ways. First of all, our finding that reversal strategies yield significant returns net of trading costs presents a serious challenge to standard rational asset pricing models. Our findings also have important implications for the practical implementation of reversal strategies. The key lesson is that investors striving to earn superior returns by engaging in reversal trading are more likely to realize their objectives by using portfolio construction rules that limit turnover and by trading in liquid stocks with relatively low trading costs. Our study adds to the vast amount of literature on short-term reversal or contrarian strategies [see, e.g., Fama (1965), Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990), Jegadeesh and Titman (1995a,b), Chan (2003), Subrahmanyam (2005), and Gutierrez and Kelley (2008)]. Our work is also related and contributes to a recent strand in the literature that re-examines market anomalies after incorporating transaction costs [see, e.g., Lesmond, Schill and Zhou (2004), Korajczyk and Sadka (2004), Avramov, Chordia and Goyal (2006) and Chordia, Goyal, Sadka, Sadka and Shivakumar (2009)].

Our results also have important implications for several explanations that have been put forward in the literature to explain the reversal anomaly. In particular, our finding that net reversal profits are large and positive among large-cap stocks over the most recent decade in our sample, during which market liquidity dramatically increased, rules out the explanation that reversals are induced by inventory imbalances by market makers and that the contrarian profits are a compensation for bearing inventory risks [see, e.g., Jegadeesh and Titman (1995b)]. Also, our finding that reversal profits are not convincingly larger for the 1,500 largest U.S. stocks than for the 500 and even 100 largest stocks is inconsistent with the notion that nonsynchronous trading contributes to contrarian profits [see, e.g., Lo and MacKinlay (1990) and Boudoukh, Richardson and Whitelaw (1994)] as this explanation predicts a size-related lead-lag-effect in stock returns and higher reversal profits among small-cap stocks.

Our second main contribution is that we not only employ the trading costs estimates from the Keim and Madhavan (1997) model that are typically used in this stream of literature, but that we also use estimates that were provided to us by Nomura Securities. Despite the fact that most researchers now seem to acknowledge the importance of taking trading costs into account when evaluating the profitability of investment strategies, only very little is documented in the academic literature on how these costs should be modelled. Perhaps the most authoritative research in this field is the work of Keim and Madhavan who modelled market impact as well as commission costs for trading NYSE-AMEX stocks during 1991 to 1993. However, since markets have undergone important changes over time one may wonder if the parameter estimates of Keim and Madhavan can be used to estimate trading costs accurately also over more recent periods. Another concern with the Keim and Madhavan model relates to the functional form that is imposed on the relation between market capitalization and trading costs. Later in the chapter we provide some detailed examples which indicate that trading costs estimates resulting from the Keim and Madhavan model should be interpreted with caution in some cases because of these issues. For example, the model systematically yields negative cost estimates for a large group of stocks over the most recent period. We believe that our study makes a significant contribution to the literature on evaluating the profitability of investment strategies by providing a comprehensive overview of trading costs estimates from Nomura Securities for S&P1500 and S&P500 stocks during the period 1990 to 2009. Moreover, the trading cost schemes we publish in this study are set up in such a way that other researchers can employ them in their studies as the schemes merely require readily-available volume data for their usage.

An additional attractive feature of the trading cost model used by Nomura Securities is that it has also been calibrated using European trade data. This enables us to investigate trading costs and reversal profits in European equity markets as well. To our best knowledge, this study is the first to provide a comprehensive overview of trading costs and to investigate trading cost impact on reversal profits in European equity markets.

3.2. Stock data

For our U.S. stock data we use return data for the 1,500 largest stocks that are constituents of the Citigroup U.S. Broad Market Index (BMI) during the period January 1990 and December 2009. We intentionally leave out micro-cap stocks from our sample that are sometimes included in other studies to ensure that our findings are not driven by market micro-structure concerns. For our European stock data we use return data for the 1,000 largest stocks that were constituents of the Citigroup European Broad Market Index during the period January 1995 and December 2009. The reason why we start in 1995 instead of 1990 as we do in our analysis using U.S. data is that the trading cost model of Nomura is not accurately calibrated to estimate trading costs for European stocks before 1995. Daily stock returns including dividends, market capitalizations and price volumes are obtained from the FactSet Global Prices database.[42]

We visually inspect various measures of liquidity for both stock markets, including market capitalization, daily trading volumes, turnover, and Amihud's (2002) illiquidity measure.[43] When we compare our U.S. sample to the one studied by Avramov, Chordia and Goyal (2006), our sample seems to be more liquid. For example, when we consider the stocks' illiquidity in our sample we find a median illiquidity measure of 0.02 in 1990 that decreases to 0.001 in 2009. Avramov, Chordia and Goyal (2006) report this figure to be 0.05 for the most liquid group of stocks in their sample. For the least liquid group of stocks the authors even report average illiquidity of 10.8. This figure basically implies that the price impact resulting from trading one million USD in these stocks is roughly 10 percent. We do not observe such large numbers for illiquidity in our sample. We believe that the largest portion of the differences in liquidity between our sample and that of Avramov, Chordia and Goyal (2006) can be attributed to the fact that we investigate a more recent period of time during which markets were much more liquid. In addition, our sample does not include micro-cap stocks.

Next, we compare the liquidity of the European stock markets to that of the U.S. stock market. It appears that the European markets also have been liquid over our sample period, but that the illiquidity level is higher than for the U.S. market: the median illiquidity measure is 0.004 in 2009 for the European markets, while this figure is 0.001 for the U.S. stocks.

[42] FactSet Global Prices is a hiqh-quality securities database offered by FactSet Research Systems Inc.
[43] For the sake of brevity, we do not report these results in tabular form.

3.3. Trading cost estimates

Consistent with most of the literature we use the trading cost model of Keim and Madhavan (1997) to estimate net reversal profits for our first analyses. These trading cost estimates include commissions paid as well as an estimate of the price impact of the trades. Keim and Madhavan regress total trading costs on several characteristics of the trade and the traded stock. Appendix 3.A provides a more detailed description of the Keim and Madhaven model. An important caveat that should be taken into account when using the Keim and Madhavan (1997) model is that its coefficients are estimated over the period January 1991 through March 1993. Since markets have undergone important changes over time one may wonder if estimates resulting from the Keim and Madhavan model are also accurate over more recent periods. For example, after two centuries pricing in fractions, the NYSE and AMEX converted all of their stocks to decimal pricing in 2001 which led to a large decrease in bid-ask spreads on both exchanges. Also, increasing trading volumes over time; more competition among stock brokers; and technological improvements may have had an important impact on bid-ask spreads, market impact costs and commissions.

To cope with this issue, we asked one of world's largest stock brokers, Nomura Securities, if they could provide us with trading cost estimates for stocks that are constituents of the S&P1500 index over our sample period January 1990 through December 2009. The Nomura trading cost model is calibrated in every quarter over the period 1995 to 2009. Appendix 3.B provides a detailed description of the Nomura model. As estimates for broker commissions a 5 basis points rate per trade is used during the 1990s and a 3 basis points rate over the most recent 10 years of our sample period.

An important aspect that came to light in our conversations with the researchers from Nomura is that trading style may have a significant impact on trading costs. For example, technical traders that follow momentum-like strategies and have a great demand for immediacy typically experience large bid-ask costs since the market demand for the stocks they aim to buy is substantially larger than the supply, and vice versa for sell transactions. In their study, Keim and Madhavan (1997) also find that technical traders generally experience higher trading costs than traders whose strategies demand less immediacy like value traders or index managers. The researchers of Nomura told us that the trading costs that are associated with a reversal strategy are likely to be somewhat lower than the estimates they provided since a reversal strategy by nature buys (sells) stocks for which the market supply (demand) is larger than the demand (supply). However, they could not provide us with an exact number to correct for this feature of reversal strategies. To be conservative we assume that there is no liquidity-provision premium involved with reversal trading.

We asked the researchers of Nomura to provide us with aggregated data in the form of average trading costs for decile portfolios of S&P1500 stocks sorted on their dollar volumes in each quarter during the period January 1990 to December 2009.[44] Trading cost estimates for an individual stock can now be derived using the stock's volume rank at a particular point in time. An attractive feature of this approach is that it only requires readily-available volume data, and not proprietary intraday data. The trading cost schemes we publish in this study also enable other researchers to employ the Nomura trading cost estimates in their studies. We also asked them to assume that the trades are closed within one day and the trade size is one million USD per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum. The assumption of such a large trade size ensures that any effects we document can be exploited by a sizable strategy. For example, a strategy that is long-short in the 20 percent losers and winners of the largest 1,500 U.S. stocks and trades one million USD per stock employs a capital of USD 300 million by the end of 2009. We use the same trade sizes when using the Keim and Madhavan (1997) model to estimate trading costs.

Table 3.1 presents an overview of the trading cost estimates we received from Nomura for S&P1500 stocks and also lists the estimates for our sample of the 1,500 largest U.S. stocks resulting from the Keim and Madhavan (1997) model. The table presents the average single-trip costs of buy and sell transactions in basis points for each year in our sample for decile portfolios of stocks sorted on their three-month median dollar trading volume.

Panel A of Table 3.1 reports the cost estimates resulting from the Keim and Madhavan (1997) model. The cost estimates for our sample of stocks during the period 1991 to 1993 seem to be close to the estimates reported by Keim and Madhavan for the median stock (see Table 3 of their paper). However, there are also a few notable observations. We find negative cost estimates for the most liquid stocks with the largest trading volumes. The number of stocks with negative trading cost estimates also increases over time. In fact, the Keim and Madhavan model yields negative cost estimates for almost half of the stocks in our sample during 2007. Panel B of Table 3.1 reports the trading cost estimates that were provided to us by Nomura for S&P1500 stocks. Interestingly, Nomura's cost estimates appear not only to be higher for the most liquid stocks with the highest trading volumes, but

[44] Because the S&P1500 Index started in 1995, we asked the researchers of Nomura to backfill their series of trading cost estimates using the 1,500 largest stocks that are constituents of the Russell Index over the period January 1990 to December 1994.

also for the least liquid stocks with the lowest trading volumes. For these stocks the cost estimates of Nomura can be up to six times higher than those resulting from the Keim and Madhavan model.

TABLE 3.1. Transaction cost estimates for the 1,500 largest U.S. stocks.
This table presents an overview of the single-trip transaction cost estimates in basis points for volume deciles of our sample of the 1,500 largest U.S. stocks resulting from the Keim and Madhavan model (Panel A) and the estimates for volume deciles of S&P1500 stocks we received from Nomura Securities (Panel B). Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Keim-Madhaven average buy and sell																					
D1 (bottom)	71	78	47	28	29	27	21	12	13	18	21	26	30	29	13	12	10	11	38	63	30
D2	82	74	53	32	33	30	20	10	14	20	27	29	38	36	15	13	9	8	37	66	32
D3	64	72	51	32	30	25	18	11	15	19	24	24	39	35	19	10	7	7	40	61	30
D4	56	53	38	30	32	25	15	12	14	18	21	29	42	32	19	15	6	8	34	58	28
D5	48	39	32	30	25	22	15	9	11	17	15	27	43	38	15	16	6	4	24	37	24
D6	38	29	23	22	20	14	10	8	8	11	15	23	41	26	14	11	6	1	16	34	18
D7	24	20	18	13	14	8	6	1	4	5	6	15	26	22	8	2	2	-6	15	28	11
D8	16	11	9	8	4	4	1	-3	-5	-6	0	13	14	10	2	-6	-11	-14	7	21	4
D9	0	-3	-5	-5	-2	-6	-6	-11	-12	-13	-10	0	3	0	-9	-17	-16	-21	-5	8	-7
D10 (top)	-20	-20	-19	-19	-17	-19	-22	-26	-28	-31	-25	-14	-5	-11	-17	-25	-26	-31	-21	-15	-20
Panel B. Nomura buy or sell																					
D1 (bottom)	86	77	83	75	73	54	52	66	53	76	65	88	80	76	76	65	53	41	51	70	68
D2	72	60	60	55	51	34	27	35	31	65	67	61	56	50	41	30	24	20	25	50	46
D3	58	50	45	41	38	23	19	22	23	47	47	37	30	24	20	17	15	14	17	33	31
D4	48	41	36	30	30	17	12	18	18	30	28	23	20	17	14	13	12	11	13	23	23
D5	41	34	30	26	25	15	14	14	17	21	19	16	15	13	12	11	10	9	11	17	19
D6	33	26	22	21	20	13	13	12	14	16	14	13	12	11	10	9	9	8	9	14	15
D7	26	23	21	18	17	11	17	11	11	13	11	10	9	9	8	8	8	7	8	11	13
D8	22	20	18	16	14	10	17	13	10	11	9	8	8	8	7	7	6	6	6	9	11
D9	17	15	14	13	13	9	11	11	10	9	7	7	7	6	6	6	6	5	6	7	9
D10 (top)	13	14	14	13	13	10	9	8	8	7	5	5	5	5	5	5	5	5	5	5	8

Once we focus on the 500 largest stocks in our sample, the differences between the trading cost estimates resulting from the Keim and Madhavan (1997) model and the Nomura model become even more extreme. Panel A of Table 3.2 reports the cost estimates resulting from the Keim and Madhavan model and Panel B the cost estimates that were provided to us by Nomura. We immediately observe that the cost estimates resulting from the Keim and Madhaven model for our sample of large-cap stocks are very low and even negative in a lot of cases. In fact, for a large number of years in our sample, trading cost estimates are negative for basically all stocks. In addition, for all deciles, Nomura's cost estimates are substantially higher than the estimates resulting from the Keim and Madhavan model. Based on the Keim and Madhavan model, the average single-trip transaction costs for the 10 percent most expensive stocks to trade are 4 basis points. This figure is substantially lower than the 6 basis points trading costs that result from the Nomura model for the 10 percent cheapest stocks.

TABLE 3.2. Transaction cost estimates for the 500 largest U.S. stocks.
This table presents an overview of the single-trip transaction cost estimates in basis points for volume deciles of our sample of the 500 largest U.S. stocks resulting from the Keim and Madhavan model (Panel A) and the estimates for volume deciles of S&P500 stocks we received from Nomura Securities (Panel B). Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million USD per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Keim-Madhaven average buy and sell																					
D1 (bottom)	14	6	2	1	8	8	2	-4	0	6	9	8	4	3	-4	-9	-11	-16	-5	51	4
D2	14	10	3	1	3	0	-1	-8	-8	-5	-4	-3	5	7	-3	-9	-12	-16	-4	46	1
D3	12	6	5	1	1	-2	-8	-11	-10	-8	-6	-3	3	-1	-8	-13	-16	-19	-2	40	-2
D4	8	7	3	0	0	-2	-7	-11	-12	-11	-11	-6	2	-1	-11	-15	-19	-19	-6	39	-4
D5	9	5	1	-2	-2	-3	-10	-12	-14	-15	-12	-10	0	-1	-11	-16	-21	-21	-10	28	-6
D6	6	1	-4	-7	-3	-7	-11	-15	-16	-16	-17	-11	2	-3	-14	-21	-18	-23	-7	26	-8
D7	1	-5	-6	-8	-5	-10	-12	-17	-17	-16	-20	-8	1	-2	-15	-16	-18	-22	-11	15	-10
D8	-7	-10	-9	-10	-9	-12	-15	-17	-19	-24	-21	-9	0	0	-14	-16	-21	-28	-8	16	-12
D9	-12	-10	-13	-15	-14	-17	-21	-25	-27	-30	-29	-16	-9	-12	-14	-24	-22	-27	-17	2	-18
D10 (top)	-24	-25	-27	-24	-24	-27	-29	-34	-38	-39	-38	-19	-4	-22	-27	-30	-32	-34	-24	-16	-27
Panel B. Nomura buy or sell																					
D1 (bottom)	23	15	13	15	22	31	25	24	23	23	34	36	34	38	40	28	19	15	13	21	25
D2	12	11	10	12	16	22	13	14	16	27	26	20	17	17	14	11	10	9	10	14	15
D3	11	10	9	11	14	14	11	17	14	16	16	13	12	12	10	9	9	8	8	12	12
D4	10	9	9	11	12	12	12	12	12	13	12	11	10	10	9	8	8	7	7	11	10
D5	9	9	8	10	11	12	12	11	10	11	10	9	9	9	8	7	7	6	7	9	9
D6	8	8	8	9	10	13	12	11	10	10	9	8	8	8	7	7	6	6	6	9	9
D7	8	8	8	9	9	11	11	10	9	11	8	7	7	7	7	6	6	6	6	8	8
D8	8	8	7	8	9	11	11	10	10	9	7	6	7	7	6	6	6	5	6	7	8
D9	7	7	7	7	9	10	9	9	9	8	6	6	6	6	6	5	5	5	5	6	7
D10 (top)	7	7	6	7	8	10	9	8	8	7	4	5	5	5	5	5	5	4	4	5	6

We offer the following explanations for these notable differences. First, the differences may be caused by the fact that the model of Nomura imposes a quadratic relation between trading volume and transaction costs while the Keim and Madhaven (1997) model imposes a logarithmic relation. While the economic intuition behind both approaches is that they try to mimic the shape of the limit order book that is deep in the front (at the best bid/offer price) and gets increasingly shallower as prices move away from the current price by imposing a convex relation between cost and volume [see, e.g., Roşu (2009)], an attractive feature of the quadratic relation over the logarithmic relation is that cost estimates cannot become negative for the most liquid stocks. When a logarithmic relation is imposed trading cost estimates can become negative. Second, the Keim and Madhavan model uses a constant negative coefficient for market capitalization. Because the average market capitalization increased significantly in our sample, cost estimates become lower over time. It should be stressed here that we did not apply scaling techniques on the coefficient estimates in the Keim and Madhavan model as is typically done in this stream of literature to inflate trading costs back in time [see, e.g., Gutierrez and Kelley (2008) and Avramov, Chordia and Goyal (2006)]. If we would have applied these scaling techniques, the resulting cost estimates would be even lower. The Nomura model can adjust to changing market conditions in our sample because it is periodically recalibrated.

The observation that trading cost estimates resulting from the Keim and Madhavan (1997) model are substantially lower than the Nomura cost estimates (and even negative in many cases) makes us believe that the trading cost estimates resulting from the Keim and Madhavan model should be interpreted with caution in some of our analyses. Of course, it should be acknowledged that the Keim and Madhavan model was originally developed to describe the in-sample relation between trading costs and stock characteristics, and not to predict stocks' out-of-sample trading costs for evaluating trading strategies. Imposing a quadratic instead of a logarithmic relation between market capitalization and trading costs would probably not increase the in-sample explanatory power of the model. The Keim and Madhavan model is therefore probably optimally specified for the purpose it was originally developed for.

An additional attractive feature of the trading cost model we obtained from Nomura Securities is that it has also been calibrated using European trade data over the period 1995 to 2009 which enables us to investigate trading costs and reversal profits in these markets. To our best knowledge, this study is the first to provide a comprehensive overview of trading costs and to investigate trading cost impact on reversal profits in European equity markets. The lower liquidity of the European markets makes us expect that trading costs in Europe are higher than in the U.S. For comparison, we list the trading costs estimates we obtained from Nomura Securities for the largest 1,000 and 600 European stocks in Table 3.3. We asked the researchers of Nomura to use the same settings to compute trading costs in Europe as they used to compute trading costs in the U.S.

When we compare the trading costs estimates for the 1,500 largest U.S. stocks to those for the 1,000 largest European stocks in Panel A of Table 3.3, it appears that trading costs are indeed higher in Europe. For example, the trading costs of the 10 percent least liquid stocks are 76 basis points for European stocks, while the costs are 64 basis points for

U.S. stocks. The differences become larger when we move to the more liquid segment of the market. For the 10 percent most liquid stocks, trading costs are even three times higher in Europe compared to the U.S. When we consider trading cost estimates for the 600 largest European stocks in Panel B of Table 3.3, we observe a very similar pattern in the sense that the most liquid U.S. stocks are significantly less expensive to trade.

TABLE 3.3. Transaction cost estimates for the 1,000 and 600 largest European stocks.
This table presents an overview of the single-trip transaction cost estimates in basis points for volume deciles of our sample of the 1,000 (Panel A) and 600 (Panel B) largest European stocks resulting from the estimates for volume deciles we received from Nomura Securities. Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. 1,000 largest European stocks																
D1 (bottom)	75	75	77	77	77	71	75	77	79	72	74	76	71	79	88	76
D2	64	64	57	62	68	64	71	74	75	68	62	53	48	71	82	66
D3	46	46	43	48	51	54	60	63	63	48	48	39	35	56	75	52
D4	38	37	35	41	41	46	50	53	52	38	42	32	30	46	66	43
D5	33	31	31	34	35	40	44	43	43	31	35	27	26	38	56	37
D6	27	28	27	28	31	34	35	36	33	27	30	24	24	32	46	31
D7	24	24	24	25	26	27	28	29	27	23	25	22	23	28	40	26
D8	22	22	22	23	23	22	23	23	23	21	22	20	20	25	31	23
D9	22	21	20	21	21	19	20	20	20	19	20	19	19	21	25	20
D10 (top)	21	20	20	20	19	17	19	19	19	18	19	18	18	20	22	19
Panel B. 600 largest European stocks																
D1 (bottom)	72	72	69	68	75	64	71	72	72	66	63	57	50	66	80	68
D2	54	51	44	50	53	55	61	62	62	48	46	33	30	48	67	51
D3	36	36	34	38	39	44	45	49	47	31	36	27	25	35	51	38
D4	30	29	29	30	32	34	36	35	39	27	29	25	24	30	42	31
D5	26	26	26	27	28	29	30	30	32	23	26	23	22	27	39	28
D6	23	24	24	25	25	24	25	26	26	21	23	21	22	26	34	25
D7	22	22	22	22	23	22	22	22	23	20	21	20	20	23	28	22
D8	22	21	21	22	21	19	20	20	21	19	20	19	18	21	25	21
D9	21	20	19	20	20	18	19	19	20	19	19	19	18	20	23	20
D10 (top)	21	20	18	19	18	16	19	19	19	18	18	18	17	19	21	19

3.4. Main empirical results

3.4.1. Reversal profits across different market cap segments

In our first analysis we evaluate reversal profits for the 1,500, 500, and 100 largest U.S. stocks. Our hypothesis is that the reported impact of trading costs on reversal profits can largely be attributed to excessively trading in small-cap stocks and that limiting the stock universe to large-cap stocks significantly reduces trading costs.

Reversal portfolios are constructed by daily sorting all available stocks into mutually exclusive quintile portfolios based on their past-week returns (i.e., five trading days). We assign equal weights to the stocks in each quintile. The reversal strategy is long (short) in the 20 percent of stocks with the lowest (highest) returns over the past week. To control for the bid-ask bounces, we skip one day after each ranking before we construct portfolios. Portfolios are rebalanced at a daily frequency. We compute the gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio in excess of the equally-weighted return of all stocks in the cross-section. In addition, we compute the long-short portfolios' turnover per week. We compute net returns for each stock at each point in time by taking the trading cost estimates listed in Tables 3.1 and 3.2. We impose that the minimum trading cost estimates resulting from the Keim and Madhavan (1997) model are zero to be conservative.

We first consider the results for a standard reversal strategy using the 1,500 largest U.S. stocks in Panel A of Table 3.4. Consistent with most of the literature we find that this strategy yields extremely large gross returns. More specifically, a reversal investment strategy that is long in the 20 percent stocks with the lowest one-week returns and short in the 20 percent with the highest returns earns a gross return of 61.7 basis points per week.

However, at the same time the reversal strategy has an extremely high portfolio turnover of 677 percent per week.[45] We find that the average holding period of a stock is less than three days. Once trading costs are taken into account the profitability of the reversal strategy completely diminishes. When we take Keim and Madhavan (1997) trading cost estimates, we document a net return of minus 66.1 basis points per week. And when we use the Nomura cost estimates, we even find a return of minus 103.7 basis points per week. These results are consistent with the findings of Avramov, Chordia and Goyal (2006).

[45] The maximum turnover of a long-short portfolio is 400 percent per day.

TABLE 3.4. Profitability of standard reversal investment strategies for the 1,500, 500 and 100 largest U.S. stocks.
This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quintiles for the 1,500 (Panel A), 500 (Panel B) and 100 (Panel C) largest U.S. stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 3.1 and 3.2. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 1,500 largest U.S. stocks					
Gross return	29.9	-31.6	61.7	8.7	677
Net return using KM estimates	-35.3	31.1	-66.1	-9.2	"
Net return using Nomura estimates	-54.6	49.6	-103.7	-14.5	"
Panel B. Standard reversal strategy for 500 largest U.S. stocks					
Gross return	35.3	-36.4	71.9	9.1	688
Net return using KM estimates	32.5	-33.6	66.4	8.4	"
Net return using Nomura estimates	-2.7	0.3	-3.0	-0.4	"
Panel C. Standard reversal strategy for 100 largest U.S. stocks					
Gross return	43.7	-40.3	84.2	9.8	711
Net return using KM estimates	42.8	-39.4	82.5	9.6	"
Net return using Nomura estimates	17.1	-14.4	31.5	3.7	"

One of the most notable observations in the previous section was that there is a highly non-linear relation between market capitalization/trading volume and trading costs such that the smallest and least liquid stocks are disproportionally expensive to trade. Especially since these stocks generally have the highest volatility and therefore have the greatest probability to end up in the extreme quantiles when stocks are ranked on past returns, a long-short reversal portfolio is typically invested in the stocks that are the most expensive to trade. While some studies report that stock anomalies are typically stronger among small-cap stocks, one may wonder if the potentially higher returns of small-cap stocks compensate for the higher trading costs of these stocks.

To investigate the impact of including small-cap stocks, we consider the results for the 500 and 100 largest U.S. stocks in Panels B and C of Table 3.4, respectively. Interestingly, the reversal strategies for the largest 500 and 100 stocks earn slightly higher returns than the reversal strategy for the largest 1,500 stocks. Moreover, it appears that the impact of trading costs on the profitability of the strategy is much lower for our samples of large-cap stocks. Given the large number of negative cost estimates we found using the Keim and Madhavan (1997) model for the largest 500 stocks, it is not surprising to see that the net return of the reversal strategy computed using these cost estimates are very close to the strategy's gross return since we impose minimum trading costs of zero. However, also when we use the trading cost estimates of Nomura, it appears that trading costs have a much smaller impact on reversal profits once small-cap stocks are excluded. The net return of minus 3.0 basis points per week of the strategy for the 500 largest stocks indicates that trading costs consume roughly 75 basis points of the strategy's gross return. For the 100 largest stocks this figure is 53 basis points. For our sample of the 1,500 largest stocks trading impact is more than three times larger at 165 basis points.

The results from this analysis indicate that reversal profits are also observed among the largest stocks. In fact, reversal profits appear to be the highest among this group of stocks. Our finding that reversal strategies can yield a significant return of more than 30 basis points per week net of trading costs presents a serious challenge to standard rational asset pricing model and has important implications for the practical implementation of reversal investment strategies. The key lesson is that investors striving to earn superior returns by engaging in reversal trading are more likely to realize their objectives by trading in liquid stocks with relatively low transaction costs.

3.4.2. Reducing reversal strategies' turnover by "smart" portfolio construction

Another important reason why trading costs have such a large impact on reversal profits has to do with the way the reversal portfolios are typically constructed. Reversal portfolios are constructed by taking a long position in losers and a short position in winners. Then, at a pre-specified interval the portfolio is rebalanced and stocks that are no longer losers are sold and replaced by newly bottom-ranked stocks. And vice versa, stocks that are no longer winners are bought back and replaced by newly top-ranked stocks. While this portfolio construction approach is standard in the academic literature to investigate stock market anomalies, it is suboptimal when a real-live investment strategy is evaluated and trading costs are taken into account. Namely, replacing stocks that are no longer losers (winners) by newly bottom (top)-ranked stocks only increases the profitability of reversal strategies if the difference in expected return between the stocks is larger than the costs associated with the transactions.

In many cases, however, the costs of the rebalances will be larger than the incremental return that is earned by the stock replacements. For example, for our universe of the 1,500 largest stocks we found that past loser stocks on average earn a gross excess return of roughly 6 basis points over the subsequent day while stocks in the next quintile earn 1 basis point. On average, loser (winner) stocks remain ranked in the top (bottom) quintile for a period of three days. Consequently, replacing a stock that moved from the top quintile to the second quintile only increases the profitability of the reversal strategy if the costs of the buy and sell transactions are less than 15 [= (6 - 1) * 3] basis points together. When we consider the trading cost estimates in Tables 3.1 and 3.2, however, we see that single-trip costs are larger than 7.5 basis points in many cases. Therefore a portfolio construction approach that directly sells (buys back) stocks that are no longer losers (winners) is likely to generate excessive turnover and unnecessarily high transaction costs.

A naive approach to cope with this problem would be to lower the rebalancing frequency. However, with this approach one runs the risk to hold stocks that have already reverted. Namely, a loser (winner) stock at a specific point in time might rank among the winner (loser) stocks within the interval at which the portfolio is rebalanced and might therefore have a negative (positive) expected return. In fact, the portfolio weights of loser stocks that have reverted become larger and thereby exacerbate this effect.

We propose a slightly more sophisticated approach that waits to sell (buy back) stocks until they are ranked among the 50 percent of winner (loser) stocks ranked on past return. These stocks are then replaced by the stocks with the lowest (highest) past-week return at that time and not yet included in the portfolio. As a consequence, this "smart" approach has a substantially lower turnover than the standard approach to construct long-short reversal portfolios. It is important to note that our “smart” approach holds the same number of stocks in the portfolio as the standard approach, but that the holding period with the “smart” approach is flexible for each stock with a minimum of one day and a maximum of theoretically infinity.

We now use the slightly more sophisticated portfolio construction approach outlined above to evaluate reversal profits for our samples of the 1,500, 500, and 100 largest U.S. stocks. Our hypothesis is that trading costs can significantly be reduced without giving up too much of the gross reversal profits when our slightly more sophisticated portfolio construction algorithm is applied.

We first consider the results for our sample of the 1,500 largest stocks in Panel A of Table 3.5. Indeed, the “smart” portfolio construction approach appears to successfully reduce turnover and thereby the impact of trading costs on reversal profits. While the turnover of the standard reversal strategy for the 1,500 largest stocks is 677 percent per week, this figure is 325 percent for the “smart” approach. We find that the effective holding period of a stock on average is approximately six days for this strategy. And while trading costs, estimated using the Keim and Madhavan (1997) model, consume 128 basis points of reversal gross returns of the standard reversal strategy, this figure is 61 basis points for the “smart” approach. We find a similar impact when we use the Nomura trading cost estimates. While trading costs consume 165 basis points for the standard reversal strategy, this figure is 77 basis points for the “smart” approach. All in all, it appears that using a slightly more sophisticated portfolio construction approach when engaging in short-term reversal strategies can have a significant impact on trading costs.

TABLE 3.5. Profitability of “smart” reversal investment strategies for the 1,500, 500 and 100 largest U.S. stocks.
This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal portfolios containing 20 percent of the 1,500 (Panel A), 500 (Panel B) and 100 (Panel C) largest U.S. stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock’s volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 3.1 and 3.2. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model.

	Return long (bps)	Return short (bps)	Return long-short	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks					
Gross return	27.7	-31.9	59.8	8.8	325
Net return using KM estimates	-2.9	-1.4	-1.5	-0.2	"
Net return using Nomura estimates	-10.9	6.8	-17.6	-2.6	"
Panel B. Smart reversal strategy for 500 largest U.S. stocks					
Gross return	30.7	-34.0	65.0	8.7	326
Net return using KM estimates	29.4	-32.7	62.3	8.4	"
Net return using Nomura estimates	13.7	-16.8	30.5	4.1	"
Panel C. Smart reversal strategy for 100 largest U.S. stocks					
Gross return	40.9	-36.7	77.9	9.4	337
Net return using KM estimates	40.5	-36.3	77.1	9.3	"
Net return using Nomura estimates	28.6	-24.4	53.1	6.4	"

Next, we consider the results for the 500 and 100 largest U.S. stocks in Panels B and C of Table 3.5. Also for these samples we see that the “smart” portfolio construction approach appears to successfully reduce turnover. More specifically, while the standard reversal strategies have turnovers of 688 and 711 percent per week, these figures are 326 and 337 percent for the “smart” reversal strategies applied on the 500 and 100 largest stocks, respectively. Interestingly, the gross returns of the “smart” strategies are only marginally lower than the returns we observed earlier for the standard reversal strategies. When net returns are computed using the Nomura model we find that trading costs now consume only 34 basis points of the strategy's gross return for the 500 largest U.S. stocks. This figure is 75 basis points for the standard reversal strategy. We observe a similar reduction for our sample of the 100 largest U.S. stocks. The resulting reversal profits range between 30 and 50 basis points per week and are highly significant from both a statistical as an economical point of view.

3.4.3. Reversal profits in European markets

Proceeding further we evaluate reversal profits in European stocks markets. Only a small number of studies have investigated short-term reversal strategies in non-US equity markets. Chang, McLeavey and Rhee (1995) find abnormal profits of short-term contrarian strategies in the Japanese stock market. Schiereck, DeBondt and Weber (1999) and Hameed and Ting (2000) find the same in the German and Malaysian stock markets, respectively. And Griffin, Kelly and Nardari (2010) investigate reversal profits in 56 developed and emerging countries.

Because European markets are less liquid than the U.S. market we expect the impact of trading costs on reversal profits to be larger in Europe. Using the methodology outlined in the previous section, we construct quintile portfolios for the 1,000, 600 and 100 largest European stocks to compute the returns of long-short reversal portfolios. Additionally, we apply the "smart" portfolio construction for these stock samples. For all reversal strategies we compute gross returns, and returns net of trading costs using the estimates from the Nomura model listed in Table 3.3. The results of this analysis are presented in Table 3.6.

It appears that gross reversal profits are also very large in Europe and in the same order of magnitude as in the U.S. However, as we expected, the impact of trading costs appears to be larger in Europe. For our universes of the 1,000 and 600 largest European stocks we do not find positive returns net of trading costs. Only when we exclusively focus on the 100 largest stocks and apply the "smart" portfolio construction, we document significantly positive net reversal profits up to 20 basis points per week.

All in all, the European results exhibit the same features as our U.S. results: once we move more towards the large-cap segment of the market and limit turnover by "smart" portfolio construction, reversal strategies yield significant returns net of trading costs. At the same time, trading costs have a larger impact on reversal profits in Europe than in the U.S.

TABLE 3.6. Profitability of reversal investment strategies for the 1,000, 600 and 100 largest European stocks.

This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal strategies for the 1,000, 600 and 100 largest European stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Table 3.3. Panels A, C and E present the results using a standard portfolio construction approach that is long (short) in the 20 percent of stocks with the lowest (highest) returns over the past week. Panels B, D and E show the results for a slightly more sophisticated portfolio construction approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 1,000 largest European stocks					
Gross return	24.6	-25.3	50.0	7.7	672
Net return using Nomura estimates	-113.4	106.5	-217.5	-33.4	"
Panel B. Smart reversal strategy for 1,000 largest European stocks					
Gross return	28.2	-27.6	56.0	9.0	319
Net return using Nomura estimates	-36.0	36.4	-72.1	-11.6	"
Panel C. Standard reversal strategy for 600 largest European stocks					
Gross return	34.3	-34.6	69.2	9.6	683
Net return using Nomura estimates	-81.3	76.8	-156.9	-21.8	"
Panel D. Smart reversal strategy for 600 largest European stocks					
Gross return	35.0	-34.2	69.5	10.0	323
Net return using Nomura estimates	-18.6	19.8	-38.3	-5.5	"
Panel E. Standard reversal strategy for 100 largest European stocks					
Gross return	48.0	-48.1	96.5	9.8	700
Net return using Nomura estimates	-24.9	22.9	-47.7	-4.9	"
Panel F. Smart reversal strategy for 100 largest European stocks					
Gross return	46.3	-43.8	90.5	9.5	332
Net return using Nomura estimates	11.9	-9.7	21.6	2.3	"

3.5. Follow-up empirical analyses

3.5.1. Weekly rebalancing

In our first follow-up empirical analysis we evaluate a naive portfolio construction approach that reduces the turnover of reversal strategies by decreasing the rebalancing frequency to five days. All the other settings are exactly the same as with the standard approach. As mentioned earlier, the main disadvantage of this approach compared to the "smart" portfolio construction approach described in the previous section is that one runs the risk to hold stocks that have already reverted. We evaluate this portfolio construction approach for our samples of the largest 1,500, 500 and 100 largest U.S. stocks. The results are in Table 3.7.

TABLE 3.7. Profitability of reversal investment strategies using a five-day rebalancing frequency.
This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quintiles using a five-day rebalancing frequency for the 1,500 (Panel A), 500 (Panel B) and 100 (Panel C) largest U.S. stocks. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Tables 3.1 (for the 1,500 largest U.S. stocks) and 3.2 (for the 500 and 100 largest U.S. stocks).

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 1,500 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	18.6	-22.5	41.2	7.3	306
Net return using Nomura estimates	-17.6	13.9	-31.4	-5.6	"
Panel B. Standard reversal strategy for 500 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	20.2	-23.7	44.0	7.1	310
Net return using Nomura estimates	3.5	-7.1	10.6	1.7	"
Panel C. Standard reversal strategy for 100 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	25.3	-26.7	52.2	7.9	315
Net return using Nomura estimates	13.7	-15.3	29.0	4.4	"

It appears that using a five-day rebalancing frequency indeed substantially lowers portfolio turnover. For example, the turnover of the standard reversal strategy for the 1,500 largest stocks is 677 percent per week. This figure is 306 percent per week using a five-day rebalancing frequency. Also for our samples of the largest 500 and 100 stocks, the turnover of reversal strategies that use a five-day rebalancing frequency is less than half of the turnover of strategies that rebalance at a daily frequency. As a consequence, the impact of trading costs is substantially lower for these strategies. Nonetheless, the net returns of the weekly reversal strategy for the 1,500 largest stocks are significantly negative because the gross returns of the strategy are also much lower than for the daily strategy. While the daily strategy yields a gross return of 61.7 basis points per week, the weekly strategy yields only 41.2 basis points. For our samples of the largest 500 and 100 stocks we observe similar effects: trading costs become substantially lower when the rebalancing frequency is decreased to five days, but so do gross returns. The effects seem to offset each other such that net reversal profits remain in the same order of magnitude.

3.5.2. Subperiod analyses

We continue our empirical analysis by performing two subperiod analyses. First, we investigate reversal profits over the most recent decade in our sample (i.e., January 2000 to December 2009). We conjecture that it might well be the case that the decimalization of the quotation systems and the increase in stock trading volumes have affected the profitability of reversal profits. Additionally, the Adaptive Market Hypothesis of Lo (2004) states that the public dissemination of an anomaly may affect its profitability. We conjecture that it could well be the case that increased investment activities by professional investors such as hedge funds have arbitraged away a large portion of the anomalous profits of reversal strategies after publications on the reversal effect in the 1990s. The results of this analysis are presented in Panels A, B and C in Table 3.8.

It appears that the net profitability of our “smart” reversal investment strategy is quite constant over our sample period. For the 1,500 largest stocks, the “smart” reversal strategy yields a negative net return of minus 27.9 basis points per week in the most recent decade. For our sample of the 500 largest stocks, the net return decreased from 30.5 to 22.1 basis points per week. And for our sample of the largest 100 stocks, the net return slightly increased from 53.1 basis points to 59.0 basis points per week.

In our second subperiod analysis we evaluate reversal profits when leaving out the dotcom bubble years (i.e., January 1999 to December 2001) and the credit crisis (i.e., January 2008 to December 2009) from our sample. Our concern is that the trading cost models we employ underestimate costs during crises periods and reversal profits are exacerbated. The results of this analysis are reported in Panels D, E, and F of Table 3.8. Observing net reversal profits of minus 17.8, 23.2 and 34.8 basis points per week for the 1,500, 500 and 100 largest

U.S. stocks, respectively, we conclude that the reversal profits are constant over time and also highly profitable during non-crises periods.

TABLE 3.8. Profitability of reversal investment strategies over subperiods
This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on a reversal strategy over the period January 2000 to December 2009 (Panels A, B and C) and over our full sample period excluding the dot-com bubble from January 1999 to December 2001 and the credit crisis from January 2008 to December 2009 (Panels D, E and F). In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Tables 3.1 and 3.2.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks over the period 2000 to 2009					
Gross return	10.5	-22.6	33.2	2.7	317
Net return using Nomura estimates	-19.4	8.5	-27.9	-2.3	"
Panel B. Smart reversal strategy for 500 largest U.S. stocks over the period 2000 to 2009					
Gross return	22.2	-30.7	53.0	4.0	320
Net return using Nomura estimates	7.1	-14.9	22.1	1.7	"
Panel C. Smart reversal strategy for 100 largest U.S. stocks over the period 2000 to 2009					
Gross return	40.0	-38.3	78.6	5.5	329
Net return using Nomura estimates	30.3	-28.5	59.0	4.1	"
Panel D. Smart reversal strategy for 1,500 largest U.S. stocks during non-crises periods					
Gross return	29.1	-31.8	61.1	12.1	325
Net return using Nomura estimates	-10.4	7.4	-17.8	-3.5	"
Panel E. Smart reversal strategy for 500 largest U.S. stocks during non-crises periods					
Gross return	27.5	-29.6	57.3	10.6	326
Net return using Nomura estimates	10.6	-12.6	23.2	4.3	"
Panel F. Smart reversal strategy for 100 largest U.S. stocks during non-crises periods					
Gross return	31.9	-28.4	60.4	9.6	337
Net return using Nomura estimates	19.1	-15.7	34.8	5.5	"

3.5.3. "Smart" portfolio construction using alternative trade rules

Next we examine the sensitivity of our findings to alternate portfolio construction rule choices. More specifically, we evaluate reversal profits for the 500 largest U.S. stocks that sell (buy back) stocks once their rank on past-week return is above (below) the 30th (70th) percentile; the 40th (60th) percentile; the 60th (40th) percentile; the 70th (30th) percentile; and the 80th (20th) percentile.

TABLE 3.9. "Smart" portfolio construction using alternative trade rules.
This table presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal strategies relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked above (below) the 30th (70th) percentile (Panel A); the 40th (60th) percentile (Panel B); the 60th (40th) percentile (Panel C); the 70th (30th) percentile (Panel D); and the 80th (20th) percentile (Panel E). Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Table 3.2.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 500 largest U.S. U.S. stocks using 30/70 trade rule					
Gross return	34.0	-37.2	71.5	9.1	479
Net return using Nomura estimates	8.1	-11.9	20.1	2.6	"
Panel B.Smart reversal strategy for 500 largest U.S. U.S. stocks using 40/60 trade rule					
Gross return	32.1	-35.8	68.2	8.9	387
Net return using Nomura estimates	11.5	-15.4	27.0	3.5	"
Panel C. Smart reversal strategy for 500 largest U.S. U.S. stocks using 60/40 trade rule					
Gross return	30.9	-33.0	64.1	8.9	275
Net return using Nomura estimates	16.7	-18.5	35.2	4.9	"
Panel D.Smart reversal strategy for 500 largest U.S. U.S. stocks using 70/30 trade rule					
Gross return	28.1	-30.5	58.7	8.6	225
Net return using Nomura estimates	16.7	-18.6	35.3	5.2	"
Panel E. Smart reversal strategy for 500 largest U.S. U.S. stocks using 80/20 trade rule					
Gross return	24.3	-27.3	51.7	8.2	170
Net return using Nomura estimates	15.8	-18.3	34.2	5.4	"

The results in Panel A of Table 3.9 point out that reducing portfolio turnover has a large impact on net reversal profits. Once we require loser (winner) stocks with a rank above (below) the 30th (70th) percentile to be sold (bought back), net reversal profits become highly significant at 20.1 basis points per week. This compares to minus 3 basis points per week for the standard reversal strategy (see Table 3.4). While gross returns become somewhat lower when turnover is reduced, the impact of trading costs on performance becomes substantially smaller at the same time. The optimum in terms of net return is reached using a trade rule that sells (buys back) stocks once their rank on past-week return is above (below) the 70th (30th) percentile. Interestingly, it appears that reversal profits are both statistically and economically highly significant for all trade rules, ranging from 20.1 to 35.3 basis points per week. We can therefore safely conclude that our findings are robust to our choice of trade rule.

3.5.4. Fama-French regressions

To investigate to which extent reversal profits can be attributed to exposures to common risk factors we regress gross and net returns of the "smart" long-short reversal portfolios for the largest 1,500, 500 and 100 U.S. stocks on the Fama-French risk factors (French, 2010) for market, size and value [see, e.g., Fama and French (1993, 1995, 1996)]:

(3.1) $$r_{i,t} = a + b_1 sRMRF_t + b_2 SMB_t + b_3 HML_t + \varepsilon_{i,i} ,$$

where $r_{i,t}$ is the return on reversal strategy *i* in month *t*, $RMRF_t$, SMB_t and HML_t are the returns on factor-mimicking portfolios for the market, size and value in month *t*, respectively, a , b_1 , b_2 and b_3 are parameters to be estimated, and $\varepsilon_{i,t}$ is the residual return of strategy *i* in month *t*. The coefficient estimates and adjusted R-squared values from these regressions are listed in Table 3.10.

Panel A presents the results for the 1,500 largest U.S. stocks, Panel B presents the results for the 500 largest U.S. stocks, and Panel C presents the results for the 100 largest U.S. stocks. In all cases the explanatory power of the Fama-French risk factors is very small. The highest adjusted R-squared value we observe is 5 percent. We conclude that reversal profits are unrelated to exposures to common risk factors.

3.6. Implications for explanations for reversal effects

Our findings have important implications for explanations that have been put forward in the literature to explain the reversal anomaly. Short-term stock reversals are sometimes regarded as evidence that the market lacks sufficient liquidity to offset price effects caused by unexpected buying and selling pressure and that market makers set prices in part to control their inventories. Grossman and Miller (1988) and Jegadeesh and Titman (1995b) argue that the reversals are induced by inventory imbalances by market makers and the contrarian profits are a compensation for bearing inventory risks. Related to this stream of literature, Madhavan and Smidt (1993), Hasbrouck and Sofianos (1993), Hansch, Naik and Viswanathan (1998), and Hendershott and Seasholes (2006) find that prices quoted by dealers are inversely related to their inventory supporting the notion that dealers actively manage their inventories. This liquidity explanation projects that reversals should have become smaller over time since market liquidity dramatically increased. It also predicts that reversals are stronger for small-cap stocks than large-cap stocks that typically have lower turnover. In fact, under the liquidity hypothesis reversals may even not be present among large-cap stocks at all. However, our findings that net reversal profits are large and positive for the 500 and 100 largest U.S. stocks and did not diminish over the second decade in our sample rules out this explanation.

TABLE 3.10. Fama-French regressions.

This table presents the coefficient estimates and adjusted R-squared values of Fama-French regressions of weekly gross and net returns of the long-short portfolio based on reversal portfolios containing 20 percent of the 1,500 (Panel A), 500 (Panel B) and 100 (Panel C) largest U.S. stocks on the Fama-French risk factors (French, 2010) for market, size and value [see, e.g., Fama and French (1993, 1995, 1996)]:

(3.1) $r_{i,t} = a + b_1 sRMRF_t + b_2 SMB_t + b_3 HML_t + \varepsilon_{i,i}$,

where $r_{i,t}$ is the return on reversal strategy i in month t, $RMRF_t$, SMB_t and HML_t are the returns on factor-mimicking portfolios for the market, size and value in month t, respectively, a, b_1, b_2 and b_3 are parameters to be estimated, and $\varepsilon_{i,t}$ is the residual return of strategy i in month t. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Tables 3.1 and 3.2.

	Alpha (bps)	t-stat	RMRF	SMB	HML	Adj.Rsq
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks						
Gross return	60.9	9.2	0.1	-0.2	0.0	5%
Net return using Nomura estimates	-16.3	-2.5	0.1	-0.2	0.0	5%
Panel B. Smart reversal strategy for 500 largest U.S. stocks						
Gross return	66.8	9.1	0.1	-0.2	0.0	3%
Net return using Nomura estimates	32.6	4.4	0.1	-0.2	0.0	3%
Panel C. Smart reversal strategy for 100 largest U.S. stocks						
Gross return	80.7	9.9	0.1	-0.2	-0.1	2%
Net return using Nomura estimates	56.1	6.8	0.1	-0.2	-0.1	2%

Another explanation for reversal effects that has been put forward in the literature is from Lo and MacKinlay (1990) and Boudoukh, Richardson and Whitelaw (1994) who note that nonsynchronous trading contributes to contrarian profits. This explanation assumes information diffuses gradually in financial markets and that large-cap stocks react more quickly to information than small-cap stocks that are covered by fewer analysts. As a consequence of this, the returns of large-cap stocks might lead the returns of small-cap stocks. However, our finding that reversal profits are smaller for the 1,500 largest U.S. stocks than for the 500 and 100 largest stocks is inconsistent with this explanation since nonsynchronous trading predicts a size-related lead-lag-effect in stock returns and higher reversal profits among small-cap stocks.

The only explanation that has been put forward in the literature whose projections are not inconsistent with our findings is the behavioral explanation that market prices tend to overreact to information in the short run [see, e.g., Jegadeesh and Titman (1995a)]. It should be stressed that our study does not provide any direct evidence supporting this behavioral hypothesis. Of course, it is not our goal to explain the reversal effect in this study; our main point is to show that reversal profits are present after trading costs. Nonetheless, we believe that our results help to better understand the reversal anomaly since it rules out several competing explanations that have been put forward in the literature.

3.7. Summary and concluding comments

This study shows that the finding that trading costs prevent profitable execution of reversal investment strategies can largely be attributed to excessively trading in small-cap stocks. Excluding small-cap stocks and applying a slightly more sophisticated portfolio construction approach to reduce turnover when engaging in reversal trading has a tremendous impact on the returns that reversal investment strategies deliver net of transaction costs. Our finding that reversal strategies generate 30 to 50 basis points per week net of transaction costs poses a serious challenge to standard rational asset pricing models and has important implications for the practical implementation of reversal investment strategies. Our results also have important implications for several explanations that have been put forward in the literature to explain the reversal anomaly.

Another important issue that came to light in this study is that trading cost estimates of the Keim and Madhavan (1997) model that are typically used in this stream of literature to evaluate the profitability of trading strategies net of transaction costs should be interpreted with caution in some cases. More specifically, it seems that cost estimates of this model are systematically biased downwards and can even become negative. The comprehensive overview presented in this study on trading costs estimates resulting from the proprietary transaction cost model of Nomura Securities provides opportunities for future research to re-evaluate the profitability of investment strategies based on well-documented anomalies.

3.A. Keim and Madhavan (1997) model

As Avramov, Chordia and Goyal (2006) do in their study, we employ the regression results of Keim and Madhavan to estimate the transaction costs involved with reversal investment strategies. Using the results in Table 5 of Keim and Madhavan (1997) we obtain our estimates of buyer and seller trading costs:

$$(3.2)\ \hat{C}^{Buy}{}_i = 0.767 + 0.336\,D^{NASDAQ}{}_i + 0.092\,\frac{1}{mcap_i}Trsize_i - 0.084\log mcap_i + 13.807\left(\frac{1}{P_i}\right)$$

$$(3.3)\ \hat{C}^{Sell}{}_i = 0.505 + 0.058\,D^{NASDAQ}{}_i + 0.214\,\frac{1}{mcap_i}Trsize_i - 0.059\log mcap_i + 6.537\left(\frac{1}{P_i}\right)$$

where $\hat{C}^{Buy}{}_i$ and $\hat{C}^{Sell}{}_i$ are the estimated total trading costs for stock *i* in percent for either a buyer-initiated or seller-initiated order, respectively. $D^{NASDAQ}{}_i$ is equal to one if stock *i* is a NASDAQ-traded stock and zero if stock *i* is traded on NYSE or AMEX, $mcap_i$ is the market value outstanding of stock *i*, $Trsize_i$ is the trade size of stock *i*, and P_i is the price per share of stock *i*. For our long portfolios we use $\hat{C}^{Buy}{}_i$ to open the positions in the component stocks and $\hat{C}^{Sell}{}_i$ to close the positions, vice versa for the short portfolios. Keim and Madhavan estimate the trading costs for 21 institutions from January 1991 through March 1993 using 62,333 trades.

3.B. Nomura model for trading costs

The variables that are assumed to determine trading costs in the model developed by Nomura are spread, trade size, volume and volatility:

$$(4)\quad \hat{C}_i = a + b_1 spread_i + b_2 \frac{1}{volume_i^{\,2}} Trsize_i + b_3 volatility_i + \varepsilon_i$$

where $spread_i$ is the average bid-ask spread of stock *i* over the trading day, $volume_i$ is the total executed volume for stock *i* over the trading day, $Trsize_i$ is the trade size of stock *i*, and $volatility_i$ the intra-day return volatility of stock *i* over the trading day. The Nomura trading cost model is calibrated in every quarter over the period 1995 to 2009. For each calibration, actual order flows in the previous 12 months for approximately 500,000 executed trades per time are used from the trading platform formerly owned by Lehman Brothers. Consistent with the approach of Keim and Madhavan (1997), the model of Nomura also adjusts for the relevant exchange by estimating the model coefficients per region and exchange [Tse and Devos (2004) and Gajewskia and Gresse (2007) report differences in trading costs between exchanges].

The model developed by Nomura estimates transaction costs by decomposing them into three components. The first component is the instantaneous impact due to crossing the bid-ask spread. The second component is the permanent impact which is the change in market equilibrium price due to executing a trade. Finally, the third component is the temporary impact which refers to a temporary movement of price away from equilibrium price because of short-term imbalances in supply and demand. The model does not take opportunity costs into account that result from unfilled trades.

4. Are the Fama-French factors really compensation for distress risk?[46]

In this study, we revisit the question whether the Fama-French factors are manifestation of distress risk premiums. To this end, we develop new tests specifically aimed at dissecting the Fama-French factor returns from a distress risk premium. While we find that value and small-cap exposures are typically associated with distress risk, our results also indicate that distress risk is not priced and that the small-cap and value premiums are priced beyond distress risk. Moreover, the distress risk exposures of common small-cap and value factors do not have explanatory power in asset pricing tests. Our results are robust to international out-of-sample analyses and have important implications for investors engaging in small-cap and value strategies.

4.1. Introduction

While numerous studies document that value and small-cap stocks earn abnormal positive returns, the interpretation why they do so is more controversial. The main goal of this research is to provide insight into the existence of an interaction between distress risk and the value and small-cap premiums. In other words, are these premiums compensation for distress risk?

To investigate this research question we start with setting up a comprehensive data set of different proxies for firms' distress risk for the 1,500 largest U.S. firms over the period September 1991 to December 2012. From accounting data, we measure a firm's default risk by its financial leverage. Probabilities of default are also obtained using the structural model of Merton (1974). Given the results of Anginer and Yıldızhan (2017) that credit spreads are a good proxy for financial distress, we additionally consider the difference between the bond yield and the corresponding maturity-matched treasury rate as a measure for firms' distress risk. Finally, we consider credit ratings that have been used by Avramov, Chordia, Jostova and Philipov (2007, 2009, 2013) to proxy for distress risk. We merge our distress risk data with monthly equity price data.

In our first empirical analysis we evaluate the predictive power of the variables for firms' financial distress using Moody's (2000) Accuracy Profiles. While we do find some differences between the variables, it appears that all variables have predictive power for

[46] This chapter is based on De Groot, W., and Huij, J., 2017, Are the Fama-French factors really compensation for distress risk, resubmitted to the *Journal of International Money and Finance*.

firms' financial distress. We find that structural models and credit ratings do a better job in predicting financial distress than accounting measures, and that credit spreads have some predictive value over estimates resulting from structural models and credit ratings. Although stock rankings based on these measures are positively correlated, the correlations are not very high. This result indicates that our different risk measures capture distinct dimensions of financial distress.

To investigate the interaction between the value premium and distress risk we construct rank portfolios of stocks ranked on their book-to-market ratios and distress risk to explore the relation between our measures of distress risk, valuation, and stock returns. We find no evidence supporting the pricing of distress risk, and no evidence of a positive relation between default risk and the value premium. These results hold irrespective of which measure we use for distress risk.

Also when we employ alternative methodological frameworks to investigate the interaction between the value premium and distress, we find no positive relation. When using the framework a la Lakonishok, Shleifer and Vishny (1994) we take the NBER's Business Cycle indicators for economic expansions and recessions as measures for good and bad states of the world, respectively. Using this setup, we find that value stocks outperform growth stocks both during expansions and recessions. At the same time, we generally find that high-risk stocks based on our different distress measures exhibit large underperformance during recessions corroborating our finding that our distress proxies have predictive power for financial distress. And when we use cross-sectional Fama and MacBeth (1973) regressions at the individual stock level to estimate if there is a value premium above and beyond distress risk effects, our results consistently indicate a substantial value premium and no positive relation between stock returns and distress risk exposures.

For the small-cap anomaly we also find no evidence supporting a distress risk-based explanation. While small-cap stocks do have a substantially higher probability to get into financial distress, it is not the case that small-cap stocks only yield positive abnormal returns if they run higher levels of distress risk. In fact, it seems that the size premium is concentrated in low-risk small-cap stocks. It also appears that there is a large positive small-cap premium during recessions. This is inconsistent with a risk-based explanation that projects that small caps must underperform large-cap stocks in the bad states of the world. In addition, the cross-sectional Fama and MacBeth (1973) regressions at the individual stock level show a strong size premium once corrected for distress risk. Another interesting finding of our analyses is that our results help to understand the discrepancy in the literature that several studies do not find a significant size premium after the early 1980s. We show that once distress risk is taken into account in the analyses a significant small-cap premium can be observed even after the early 1980s.

We also investigate if the large empirical explanatory power of the Fama-French (1993) SMB (Small-Minus-Big) and HML (High-Minus-Low) factors for the size and value effects can be attributed to these factors being exposed to distress risk. The typical approach in the stream of literature on empirical asset pricing to correct for the size and value effects is using the Fama-French (1993) three factor model that augments the one-factor market model with the SMB (Small-Minus-Big) and HML (High-Minus-Low) factors. Perhaps the most important reason why many researchers adopted the use of the SMB and HML factors is because of the factors' large empirical explanatory power for differences in the cross-section of stock returns. Because of the way the SMB and HML factors are constructed, we may expect the factors to be prone to distress risk. To investigate this issue we construct distress-risk neutral SMB and HML factors. We observe that the premiums of the factors do not decrease when distress-risk neutrality is imposed. At the same time, the distress-risk-neutral factors exhibit lower risk levels. Furthermore, we do not observe a deterioration of the explanatory power of the distress-risk-neutral factors for the variation in returns of the decile portfolios sorted on dividend yield and the 25 portfolios sorted on market capitalization and book-to-price from the webpage of Kenneth French.

Finally, when we expand our analyses to an international context and reperform all our tests for all stocks in the FTSE World Index, we come to exactly the same conclusions and find no relationship between distress risk and the value and size premiums. Overall, based on our results we conclude that there is no strong evidence supporting a distress risk-based explanation for the Fama-French factor premiums. Our results call for further research on the development and testing of theories that potentially provide an explanation for the small-cap and value effects.

The remainder of this chapter is organized as follows. Section 4.2 provides a literature overview. Section 4.3 describes the construction of our data set. Sections 4.4 and 4.5 present our empirical results for tests that examine if there is a relation between distress risk and the value and small-cap effects, respectively. Section 4.6 presents results for analyses that investigate if the empirical explanatory power of the SMB and HML factors can be attributed to their exposures to distress risk. Section 4.7 presents the results using the CRSP Stocks Database over the pre-1991 period. Section 4.8 presents the results for international stock markets. In Section 4.9 we expand our analyses to the profitability and investment effects recently documented by Fama and French (2015) and show that these effects can also not be attributed to distress risk. Section 4.10 presents the results of all stocks in the U.S. BMI index. Finally, Section 4.11 highlights the contributions of our study to the extant literature.

4.2. Literature review

A large group of academics and practitioners believe that the value and small-cap premiums are compensation for distress risk. Berk (1995) relates the effects to systematic risk that is unmeasured by conventional asset pricing models. Fama and French (1992) postulate that their small-cap and value factors proxy for the relative distress factor of Chan and Chen (1991), and Fama and French (1998) find that a factor model that incorporates a risk factor for relative distress captures the value premium in international equity returns. A large number of important studies in the field of empirical finance also consider the SMB (Small-Minus-Big) and HML (High-Minus-Low) factors of Fama and French (1993) to be priced risk factors [see, e.g., Zhang (2005)]. And several asset management companies point out that the higher returns they expect to earn for their investors through engaging in small-cap and value strategies stem from taking increased levels of risk.

However, empirical evidence does not appear to unambiguously indicate that the small-cap and value anomalies are related to financial distress. In addition, the literature reports inconsistent conclusions on whether distress risk is a systematic risk factor that is priced in the cross-section of stock returns. Dichev (1998) and Griffin and Lemon (2002) employ accounting models to estimate corporate bankruptcy risk and find a *negative* relation between distress risk and equity returns. The authors show that stocks with higher levels of distress risk as measured by Altman's model (1968) and Ohlson's model (1980) earn anomalously low returns and conclude that distress risk is therefore unlikely to account for the book-to-market effect. Also, Piotroski (2000) reports that financially healthy, high book-to-market firms generate higher returns than firms that have less healthy financial statements. And recently, Campbell, Hilscher and Szilagyi (2008) use a comprehensive set of accounting and equity market variables to measure distress risk and find that stocks with high risk of default deliver abnormal low returns and that returns of growth and value stocks are significantly negatively related to default risk.[47]

On the other hand, Ferguson and Shockley (2003) investigate the explanatory power of firms' leverage and distress risk (measured through Altman's (1968) model) and report that these factors subsume the explanatory power of the HML factor in explaining cross-sectional returns. Vassalou and Xing (2004) also investigate the relation between distress risk and the small-cap and value premiums and employ a structural approach to measure distress risk and use Merton's (1974) structural credit risk model based on option

[47] The negative relation between stock returns and distress risk documented by Campbell, Hilscher and Szilagyi (2008) is only observed when returns are adjusted for the three Fama and French (1992, 1993, 1996) factors.

pricing theory to compute individual firms' default probabilities. When the authors assess the effect of distress risk on equity returns, they conclude that default risk is positively priced in the stock market and that the small-cap effect is a default effect and that a large portion of the book-to-price effect can also be attributed to default risk. Chava and Purnanandam (2010) also use Merton's (1974) model to measure distress risk and investigate its relation with equity returns back to the early 1950s. They find that the underperformance of distressed stocks reported by Dichev (1998), Griffin and Lemon (2002), and Campbell, Hilscher and Szilagyi (2008) is specific to the 1980s. Once they exclude this decade from their sample, the underperformance of high-risk stocks disappears. They do not investigate if the small-cap or value anomalies are related to distress risk. More recently, Avramov, Chordia, Jostova and Philipov (2013) asses distress risk through credit downgrades and argue that value strategies derive their profitability from taking long positions in high credit risk firms that are prone to distress risk. And Kapadia (2011) reports that HML predicts firms' future failure rates.

The inconsistent conclusions that are drawn by the above mentioned studies with respect to the relation of the value premium and distress risk may be attributed to the different methods that are used to investigate the interaction between the Fama-French factors and distress risk and the different measures that are used to proxy for distress.[48] Vassalou and Xing (2004) express their concerns about the use of accounting models in estimating the default risk of equities. They argue that accounting models use backward-looking information from financial statements, while the Merton (1974) model they use in their study contains forward-looking information that is better suited for calculating the likelihood that a firm may default. More recently, Anginer and Yıldızhan (2017) criticise the use of estimated probabilities of default to proxy for distress risk as done in Dichev (1998), Griffin and Lemon (2002), and Campbell, Hilscher and Szilagyi (2008). They argue that accounting models implicitly assume that stocks with high probabilities of distress also have high exposures to systematic distress risk. The estimated probabilities of default, however, do not take into account that some portion of the distress risk may be diversified away by investors and therefore may not be priced. In addition, George and Hwang (2009) point out that a firm's estimated probability of default does not necessarily reflect the firm's exposure to the costs of financial distress, which is a better candidate for assessing the relevance of financial distress risk to security pricing. The authors argue that firms choose less leverage if their operations expose them to high financial distress costs.

[48] In this chapter we discuss the value and small-cap premiums which are constructed in the spirit of Fama and French (1992), henceforth called Fama-French factors.

Anginer and Yıldızhan (2017) not only criticize the use of accounting models to predict firm defaults, but also the use of structural models. According to the authors, structural models make simplified assumptions about the capital structure of a firm. And just like the estimated probabilities of default derived from accounting models, the probabilities resulting from structural models not necessarily capture the systematic component of distress risk; the only type of risk that should be rewarded with a premium. The authors propose corporate credit spreads to proxy for distress risk as these reflect the market consensus view of the credit worthiness of the underlying firm and contain a risk-premium for systematic risk. And although Elton, Gruber, Agrawal and Mann (2001) find that credit spreads cannot fully be explained by expected default losses, Anginer and Yıldızhan (2017) provide evidence that bond spreads contain default information above and beyond the measures commonly used in the literature. Using credit spreads, they find neither a positive, nor a negative significant relation between distress risk and equity returns. The authors, however, do not investigate the relation between the value premium and distress risk measured by credit spreads. It is currently unclear what relation will be found if credit spreads are used to proxy for financial distress.

Moreover, there are different approaches available to investigate the interaction between the Fama-French factor returns and distress risk. Vassalou and Xing (2004) employ double-sorted portfolios. An alternative approach would be to use cross-sectional Fama-MacBeth (1973) regressions at the individual stock level to estimate if there are small-cap and value premiums above and beyond distress risk effects. A third method that can be used is a conditional time series analysis in the spirit of Lakonishok, Shleifer and Vishny (1994). With this approach it is investigated if small-cap (value) stocks are riskier than large-cap (growth) stocks by testing if small-cap (value) stocks underperform large-cap (growth) stocks in the bad states of the world.

To summarize, it seems that there is no consensus in the literature on which measure best proxies distress risk and that the findings regarding the pricing of default risk are sensitive to the used risk measure. In addition, the literature is also inconclusive as to whether the small-cap and value premiums are compensation for financial distress.

4.3. Data and distress risk proxies

In this section we describe the data we use in our study and the measures we employ to proxy for distress risk. We also test the extent to which these proxies actually predict financial distress.

4.3.1. Data

Our sample covers the 1,500 largest stocks of the Citigroup US Broad Market Index (BMI) over the period September 1991 until December 2012. This universe roughly corresponds to the CRSP universe excluding the 25 percent of stocks with the smallest market capitalization over this time period and covers more than 95 percent of the total U.S. equity market capitalization. Our sample starts in 1991 because we could not obtain high-quality credit spread data before this date. We intentionally leave out micro-cap stocks from our sample to ensure that our findings are not prone to market micro-structure concerns.

4.3.2. Distress risk proxies

The first proxy we consider for distress risk to obtain a firm's probability of default is based on accounting data and measures risk through financial leverage, i.e., the firm's debt-to-assets ratio. A firm's debt-to-equity ratio is the most important component of related distress risk measures like Altman's (1968) Z-score and Ohlson's (1980) O-score used by, for example, Dichev (1998) and Griffin and Lemon (2002). We use quarterly Compustat data to construct the debt-to-assets ratio, where debt is defined as total debt including both short- and long-term debt. In case Compustat data are not available, we use annual data from Worldscope.

Our second proxy for distress risk is a firm's probability to default derived from a structural model. This probability is based on the distance-to-default measure, which we compute using a similar approach as Moody's KMV [see, e.g., Crosbie and Bohn (2003)] based on Merton's (1974) option pricing model. The input data we need to compute a firm's distance-to-default are the firm's market value of equity, its equity volatility and its book value of debt. Data on equity market values and equity returns to estimate volatilities are obtained from FactSet Prices. More specific, we define a firm's distance-to-default (DD) as follows:

$$(4.1)\quad DD = \frac{\ln(V_a / K) + (\mu - r_f - 0.5\sigma_a^2)T}{\sigma_a \sqrt{T}}$$

where V_a is the market value of a firm's assets, K its default point (or the book value of the debt for which we use total debt), σ_a the volatility of assets, μ is the excess drift in the underlying asset value which we proxy with 0.06 in line with Campbell, Hilscher and

Szilagyi (2008), r_f is the risk-free rate and we assume T to be one year. The distance-to-default measures how many standard deviations the firm is away from default. The smaller the difference between the asset value V_a and the default point K, the larger the probability on default.

As the market value of assets and the volatility of assets are not directly observable, we model these using Merton's (1974) option pricing model. In this model, the equity value of a firm is viewed as a European call option on the firm's assets where the strike price of the call option is the book value of the firm's debt. As a result, we obtain:

$$(4.2)\ V_e = V_a N(d_1) - Ke^{-r_f T} N(d_2)$$

$$d_1 = \frac{\ln(\frac{V_a}{K}) + (r_f + 0.5\sigma_a^2)T}{\sigma_a \sqrt{T}}$$

$$d_2 = d_1 - \sigma_a \sqrt{T}.$$

where V_e is the market value of equity and N is the cumulative distribution function of the standard normal distribution. As this equation has two unknowns, we use an iterative process similar to that of KMV to obtain the market value of assets V_a and the volatility of assets σ_a. First, we set the initial value for the volatility of assets equal to the standard deviation of the past 250 daily stock returns. Next, we back out the market value of assets using Equation 4.2 and compute monthly asset value returns. We can then obtain a new estimate for σ_a by calculating the standard deviation of the past twelve asset value returns, which is used for the next iteration. This procedure is repeated until the difference between two subsequent estimates for σ_a is less than 10E-4. With the resulting estimated σ_a and V_a, we compute the *DD* using Equation 4.1.

Our third measure for distress risk are credit spread data which we obtained from Barclays Capital (formally Lehman Brothers). The data cover debt issues that are constituents in the Barclays Capital Investment Grade Corporate and High Yield bond indexes. For each firm at each point in time we take the spread of the firm's debt issue with the largest amount outstanding in the Barclays indexes. Our distress proxy based on credit spread is defined as the difference between the option-adjusted bond yield and the corresponding maturity-matched treasury rate.

For our fourth proxy of distress risk, we use credit ratings issued by S&P. We merge the data of the four proxies for distress risk with monthly stock returns and book-to-market ratios. Quarterly book values are obtained from Compustat. In case Compustat data are not available, we use annual data from Worldscope.

4.3.3. Predictive power of distress risk proxies

In this subsection we test the extent to which our proxies actually predict financial distress. We consider a firm to be in financial distress if it receives a CCC credit rating or worse.[49] Under this definition, roughly 0.35 percent of the firms in our sample get into financial distress each year. This figure varies over time and peaks to 1.16 percent in 2001 and 1.62 percent in 2008 during the collapse of the IT bubble and the credit crisis, respectively. The percentage of firms that gets into financial distress in our sample seems to be somewhat lower than the failure rates reported by Campbell, Hilscher and Szilagyi (2008). This is not unexpected since our study includes fewer small-cap stocks that have been reported to run higher risks to default than large-cap stocks.

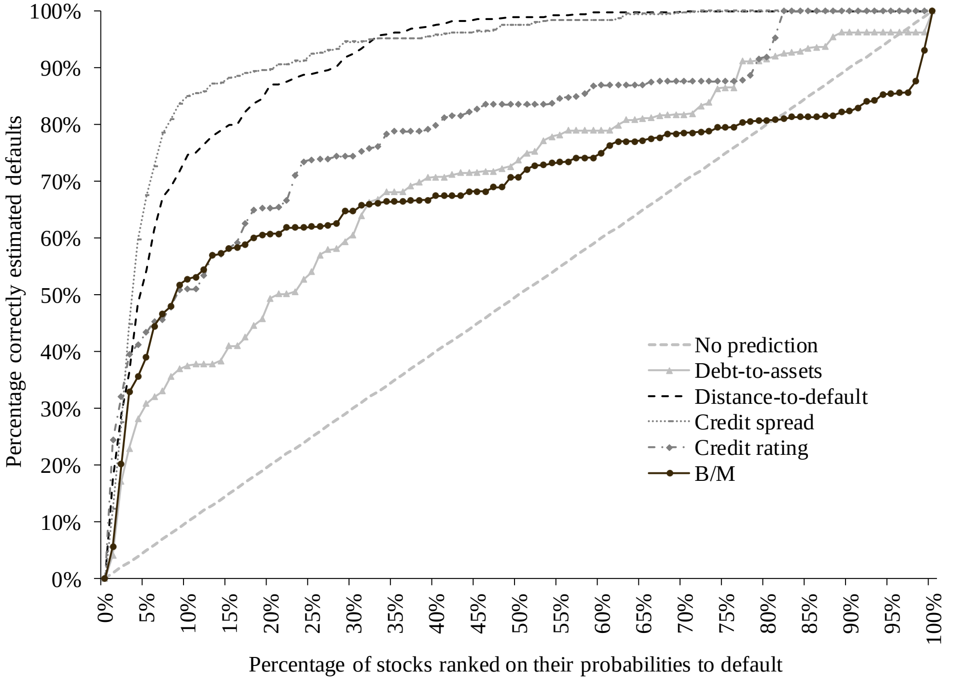
To investigate the predictive power of our measures of distress risk, we employ so-called Cumulative Accuracy Profiles [see, e.g., Moody's (2000)]. To generate the Accuracy Profiles we monthly compute what percentage of the firms that gets into financial distress in the subsequent 12 months is ranked in the top x percent of stocks on their probabilities to default estimated using our four proxies for distress risk. Here, x ranges from 1 to 100. Figure 4.1 shows the time-series averages of these percentages for our four proxies for distress risk. The Accuracy Profile of a measure that has no predictive power for financial distress follows a line from the origin of the graph and has a slope of one. The Accuracy Profile of a measure that does have predictive power for financial distress also departs from the origin, but shows a concave pattern indicating that firms are more likely to get into financial distress if their estimated probabilities of default are relatively high according to this measure.

When we consider the Accuracy Profiles of the four measures we use in this study, it appears that all of them have significant predictive power for financial distress. Roughly 50 percent of the firms that get into financial distress are ranked in the top quintile of firms based on financial leverage. The other measures even do a somewhat better job in predicting financial distress than accounting measures, since around 65 percent of the firms that get into financial distress are ranked in the top quintile on their credit ratings. This figure is close to 90 percent when firms are ranked based on their estimated probabilities of default derived

[49] We also investigate the predictive power of our distress risk proxies where we consider a firm to be in financial distress if it receives a D rating. The results of these tests are virtually identical to those resulting from tests where we consider a firm to be in financial distress if it receives a CCC rating or worse. For the sake of brevity, we do not report these results in tabular form.

from their credit spread and the structural model, indicating that these measures appear to have the highest predictive value.

FIGURE 4.1. Cumulative Accuracy Profiles.
This figure presents the Cumulative Accuracy Profiles of the book-to-market ratio (B/M), debt-to-assets ratio, distance-to-default, credit spread and credit rating. We monthly compute what percentage of the firms that gets into financial distress in the subsequent 12 month is ranked in the top x percent of stocks on their probabilities to default estimated using our four proxies for distress risk, with x ranging from 1 to 100. The curves show the time-series averages.



We also investigate the extent to which a firm's book-to-market value proxies for distress risk. To this end, we additionally compute the Accuracy Profile for this measure. The results of this analysis are also presented in Figure 4.1. It appears that a firm's book-to-market value has predictive power for financial distress. About 60 percent of the firms that get into financial distress are ranked in the top quintile of firms based on book-to-market. This result is consistent with findings of Kapadia (2011) that HML exposure predicts firms' future failure rates. However, at the same time, the convex shape of the Accuracy Profile at the bottom end of the book-to-market spectrum (top right in Figure 4.1) indicates that growth stocks with a low book-to-market ratio also have a higher probability to get into financial distress. Almost 20 percent of the firms that get into financial distress are ranked in the bottom decile based on book-to-market. So even though high book-to-market ratios seem to pick up some form of distress risk, it seems unlikely that value stocks earn higher returns than growth stocks because value stocks are exposed to higher levels of distress risk.

Finally, we consider the average rank correlations for stock rankings on the different distress risk measures. While all measures are positively correlated, the correlations are not very high ranging between 0.31 and 0.78. Financial leverage yields the lowest correlations with the other risk measures (i.e., 0.31 to 0.49). Distance-to-default, credit spread and credit rating show correlations ranging between 0.60 and 0.78. All in all, our results indicate that our risk measures capture distinct dimensions of financial distress.

4.4. The value premium and distress risk

In the following empirical analyses we investigate the relation between distress risk and the value and small-cap premiums. Given that the value premium is both economically and statistically more significant than the small-cap premium, we first consider the relation between distress risk and the value premium.

4.4.1. Distress risk characteristics of value stocks

We start our empirical analysis by investigating the distress risk characteristics of value versus growth stocks. To this end, we monthly sort stocks into quintile portfolios based on their book-to-market ratio and evaluate the portfolios' equally-weighted returns over the subsequent month, as well as their median market capitalizations, debt-to-assets ratios, distances-to-default, credit spreads and credit ratings. The results of our analysis are presented in Table 4.1. We first consider the return differential between value and growth stocks that are ranked in the first and fifth quintile portfolio, respectively. Consistent with most studies we observe a monotonically decreasing return pattern from the top to the bottom quintile portfolio and document a large value premium of 5.3 percent per annum.

We next consider the quintile portfolios' distress risk characteristics. Irrespective of the risk measure, it appears that value stocks are more exposed to distress risk than the average stock. The median debt-to-assets ratio of a value stock is 0.31 compared to 0.24 for the average stock in our sample. Value stocks are 1.8 (= 6.9 minus 5.1) standard deviations closer to their estimated point of default than the average stocks. Also, the credit spreads of firms with high book-to-market ratios are 63 (= 220 minus 157) basis points higher than those of the average stock. And firms with high book-to-market ratios generally have less favourably credit ratings, with a median rating corresponding to BBB versus an average rating of BBB+ in our sample. Additionally we observe that value stocks with a high book-to-market ratio are smaller than the average stock. We again conclude that high book-to-market ratios are related to distress risk. This finding is consistent with the results of Avramov, Chordia, Jostova and Philipov (2013) and Kapadia (2011) who document that value stocks are exposed to distress risk.

TABLE 4.1. Risk characteristics of portfolios sorted on the book-to-market ratio.
This table presents the annualized returns of quintile portfolios based on the book-to-market ratio (B/M) for the 1,500 largest U.S. stocks from September 1991 until December 2012. Portfolios are formed monthly and their returns are computed by equally weighting the firms. In addition, the table presents the following median firm characteristics of these portfolios: book-to-market ratio (B/M), debt-to-assets ratio, distance-to-default, credit spread, credit rating, and market capitalization (in billion U.S dollars).

	High B/M	2	3	4	Low B/M	High-Low
Return (annualized)	14.1%	11.6%	10.1%	8.9%	8.4%	5.3%
Excess return	2.9%	0.7%	-0.6%	-1.8%	-2.2%	5.3%
t -statistic	*1.62*	*0.60*	*-0.90*	*-1.87*	*-0.98*	*1.35*
B/M	0.84	0.57	0.41	0.28	0.13	0.71
Debt-to-assets	0.31	0.28	0.24	0.19	0.19	0.12
Distance-to-default	5.1	6.3	6.9	7.9	7.9	-2.8
Credit spread	220	171	157	138	160	60
Credit rating	BBB	BBB+	BBB+	BBB+	BBB	-
Market capitalization	1353	1528	1726	2115	2160	-807

However, the observation that value stocks have relatively higher probabilities to default is not a sufficient condition to attribute the value premium to distress disk. If the value premium indeed is a compensation for distress risk, growth stocks should have lower probabilities to default to justify their below-average returns. But when we consider the results in Table 4.1, we find that growth stocks are not substantially less exposed to distress risk compared to the average stock. In fact, growth stocks appear to be more risky than stocks ranked in the fourth quintile portfolio, as they have higher credit spreads (160 versus 138 basis points); and less favorable credit ratings (BBB versus BBB+), while they have similar debt-to-assets ratios and a similar distance-to-default. These results corroborate our previous finding that both stocks with high and low book-to-market ratios have higher probabilities to get into financial distress and indicate that a risk-based explanation of the value premium is unlikely to be true.

4.4.2. The value premium and distress risk

To investigate the relation between distress risk, valuation, and stock returns we construct triple-sorted portfolios of stocks ranked on their market capitalization, book-to-market ratios and each of our four measures of distress risk. More specifically, every month we sort stocks into terciles based on their market capitalization. Then, for each size portfolio we sort stocks into terciles based on their debt-to-assets ratio, distance-to-default, credit spread or rating. Next, we merge the small-, mid- and large-cap portfolios of high-risk stocks. We also merge the three market cap portfolios of low- and mid-risk stocks. Finally, for each aggregated tercile portfolio we sort stocks further into quintiles based on their book-to-market ratios. This triple sort ensures that the three resulting risk portfolios exhibit only minor differences in their market capitalizations and is in spirit similar to the approach used by Fama and French (1993) to construct the HML (High-Minus-Low) factor orthogonal to the size factor. We compute the equally-weighted returns over the subsequent month of the 15 portfolios. The results are listed in Table 4.2.

When we consider the results in Table 4.2 we find no evidence that default risk is a priced factor in the cross-section of equity returns: stock returns even appear to be negatively related to distress risk as we observe negative returns for most of the high-minus-low portfolios. Only the high-risk portfolio based on the debt-to-assets ratio (i.e., stocks in the “high risk/all” portfolio) earns higher returns than its low-risk counterpart. The differences between the returns of the other high- and low-risk stock portfolios range from -1.9 percent per annum when distressed risk is measured using our distance-to-default estimates to -2.5 percent using credit ratings as a measure for distress risk. Our finding that there is no positive relation between distress risk and stock returns is consistent with several other studies that look at the interaction between these variables [see, e.g., Dichev (1998), Griffin and Lemon (2002), Piotroski (2000) and Campbell, Hilscher and Szilagyi (2008)].

To answer the question if there is a relation between the value premium and distress risk we investigate if the value premium is concentrated in high-risk stocks.[50] This research question is perhaps even more interesting than our first research question, since only very few studies have looked at this relation. Note that although there is no strong positive relation between distress risk and returns on average, it could still be the case that value stocks with

[50] We believe it is more relevant to consider the return differential between high- and low-risk value stocks than the return differential between value and growth stocks within different risk segments of the market as is done in some studies. Underlying reason is that a high value-minus-growth return spread within the high-risk segment of the market is not necessarily consistent with a risk-based interpretation to the value premium, because under a risk-based interpretation the low returns of growth stocks should be concentrated in the low-risk segment of the market.

TABLE 4.2. Value effect controlled by distress risk and size
This table reports annualized returns of triple-sorted portfolios of stocks ranked on their market capitalization, book-to-market ratios and distress risk for the 1,500 largest U.S. stocks from September 1991 until December 2012. Each month, stocks are sorted into terciles based on their market capitalization. Then, for each size portfolio, stocks are sorted into terciles based on their distress risk as measured by debt-to-assets ratio, distance-to-default, credit spread or credit rating. Next, the small-, mid- and large-cap portfolios with similar risk are merged. Finally, for each tercile portfolio stocks are further sorted into quintiles based on their book-to-market ratio (B/M). Portfolio returns are computed by weighting equally the firms.

	High B/M	2	3	4	Low B/M	All
Panel A. Debt-to-assets						
Low risk	11.4%	9.9%	8.9%	6.1%	7.1%	9.0%
Mid	15.0%	11.2%	10.8%	9.1%	9.2%	11.2%
High risk	11.6%	10.7%	10.6%	8.8%	10.1%	10.6%
High-Low	0.2%	0.7%	1.6%	2.6%	2.9%	1.5%
t (High-Low)	*0.05*	*0.21*	*0.47*	*0.81*	*0.79*	*0.49*
Panel B. Distance-to-default						
Low risk	13.6%	11.8%	11.3%	10.4%	10.0%	11.6%
Mid	15.5%	11.7%	11.5%	9.1%	10.6%	11.8%
High risk	11.5%	10.5%	9.2%	7.7%	6.7%	9.4%
High-Low	-1.8%	-1.2%	-1.9%	-2.5%	-3.0%	-1.9%
t (High-Low)	*-0.49*	*-0.48*	*-0.79*	*-1.03*	*-0.97*	*-0.80*
Panel C. Credit spread						
Low risk	15.5%	12.2%	10.4%	12.1%	10.2%	12.2%
Mid	12.9%	14.8%	12.5%	9.7%	9.2%	12.0%
High risk	11.2%	9.3%	9.2%	8.0%	7.9%	9.6%
High-Low	-3.7%	-2.6%	-1.0%	-3.6%	-2.1%	-2.3%
t (High-Low)	*-0.89*	*-0.97*	*-0.44*	*-1.50*	*-0.61*	*-0.98*
Panel D. Credit rating						
Low risk	14.6%	14.3%	11.0%	12.0%	9.6%	12.5%
Mid	15.5%	14.7%	12.2%	10.8%	9.0%	12.6%
High risk	12.4%	8.8%	8.5%	7.9%	9.1%	9.6%
High-Low	-1.9%	-4.8%	-2.3%	-3.7%	-0.5%	-2.5%
t (High-Low)	*-0.60*	*-1.82*	*-0.89*	*-1.36*	*-0.14*	*-1.04*

a high distress risk earn the highest returns. Interestingly, when we consider the results in Table 4.2, we do not observe a consistent pattern that the high returns of value stocks are concentrated in the high-default-risk segment. For three of our measures we observe that high-risk value stocks earn a higher return than low-risk value stocks. Only when debt-to-assets is used as measure for distress risk, it appears that high-risk value stocks earn slightly higher returns of 0.2 per cent per annum than low-risk value stocks. Furthermore, low-risk growth stocks do not earn the lowest return. In fact, for three out of our four risk measures we find up to -3.0 percent lower returns for the high-risk growth stocks compared to low-risk growth stocks. So there seems only little evidence that the value premium is the highest for high-risk stocks, as these results are weak and only observable when the debt-to-assets ratio is used to proxy for distress risk. All in all, we conclude that no evidence is found that the value premium can be attributed to distress risk related to default.[51]

4.4.3. The value premium and distress risk during bad states of the world

So far, we constructed triple-sorted portfolios to investigate the interaction of book-to-price ratios and distress risk characteristics with stock returns. When we consider the literature on the economic origin of the value anomaly we see that several other frameworks have been employed. In the following sub-sections we investigate if the different conclusions drawn regarding the relation between the value premium and distress risk can be attributed to the use of different methodologies.

We start our analyses with a methodological setup in the spirit of Lakonishok, Shleifer and Vishny (1994). This setup relies on the premise that value stocks must underperform growth stocks in the bad states of the world when the marginal utility of wealth is high if value stocks are indeed fundamentally riskier than growth stocks. As a measure for good and bad states of the world we take the NBER's Business Cycle indicators for economic expansions and recessions, respectively.[52] This measure indicates two recessions during our sample period: the first one from March to November 2001 and the second one from December 2007 to June 2009. We evaluate the relation between distress risk and equity returns for size-neutral risk portfolios that are constructed using the procedure outlined in

[51] We also perform a follow-up empirical analysis in which we compute value-weighted (i.e., market capitalization-weighted) portfolio returns. For the sake of brevity, we do not report these results in tabular form. The main difference with the equally-weighted results is that returns on average are somewhat lower. However, the return patterns across the portfolios remain nearly unchanged.

[52] In unreported robustness tests we use the Aruoba, Diebold and Scotti (2009, ADS) Business Conditions Index as an alternative measure to distinguish between good and bad states of the world. (www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/). When the index has a value lower than the threshold of -0.8 we indicate the economy to be in a recession, consistent with Berge and Jordà (2010). According to this index there were three recessions during our sample period: from January to November 2001, August 2005, and from January 2008 to June 2009. The results of this test are qualitatively very similar to the results using the NBER's Business Cycle indicators.

the previous section. For all portfolios we compute their returns during expansions and recessions. The results are listed in Table 4.3.

TABLE 4.3. Value effect during different states of the business cycle
This table reports return characteristics of stocks during economic expansions (Panel 1) and recessions (Panel 2) based on the NBER's Business Cycle indicator. The size-neutral risk portfolios are constructed using the procedure outlined in Table 4.2. Portfolio returns are computed by weighting equally the firms.

	High B/M	2	3	4	Low B/M	All
Panel 1. Expansions						
Panel 1A. Debt-to-assets						
Low risk	15.1%	12.7%	11.8%	9.9%	11.9%	12.6%
Mid	18.8%	14.7%	14.6%	13.1%	12.6%	14.9%
High risk	15.0%	14.3%	14.2%	13.0%	13.8%	14.3%
High-Low	-0.1%	1.5%	2.1%	2.9%	1.7%	1.5%
t (High-Low)	*-0.03*	*0.41*	*0.61*	*0.82*	*0.43*	*0.47*
Panel 1B. Distance-to-default						
Low risk	16.5%	14.7%	14.6%	13.9%	13.8%	14.9%
Mid	18.0%	14.9%	14.9%	13.0%	13.3%	15.0%
High risk	15.6%	15.0%	14.2%	12.3%	12.3%	14.2%
High-Low	-0.7%	0.3%	-0.4%	-1.4%	-1.3%	-0.6%
t (High-Low)	*-0.22*	*0.16*	*-0.17*	*-0.61*	*-0.43*	*-0.28*
Panel 1C. Credit spread						
Low risk	18.3%	15.8%	14.0%	16.1%	13.3%	15.6%
Mid	18.1%	17.9%	17.1%	13.2%	13.4%	16.1%
High risk	15.3%	13.8%	14.7%	14.0%	13.9%	14.7%
High-Low	-2.5%	-1.7%	0.5%	-1.8%	0.6%	-0.8%
t (High-Low)	*-0.72*	*-0.68*	*0.25*	*-0.77*	*0.16*	*-0.36*
Panel 1D. Credit rating						
Low risk	18.9%	17.6%	14.2%	16.2%	12.6%	16.0%
Mid	19.6%	18.1%	16.4%	14.7%	12.8%	18.9%
High risk	16.7%	13.8%	13.4%	13.0%	14.6%	14.6%
High-Low	-1.9%	-3.2%	-0.7%	-2.8%	1.8%	-1.2%
t (High-Low)	*-0.68*	*-1.33*	*-0.30*	*-1.00*	*0.51*	*-0.54*

TABLE 4.3 (Continued). Value effect during different states of the business cycle

	High B/M	2	3	4	Low B/M	All
Panel 2. Recessions						
Panel 2A. Debt-to-assets						
Low risk	-14.9%	-10.3%	-12.3%	-20.2%	-24.9%	-16.4%
Mid	-11.1%	-13.1%	-15.8%	-18.6%	-15.0%	-14.5%
High risk	-13.0%	-14.7%	-14.9%	-19.7%	-15.3%	-15.1%
High-Low	2.2%	-4.9%	-2.9%	0.6%	12.8%	1.6%
t (High-Low)	*0.13*	*-0.35*	*-0.25*	*0.07*	*1.42*	*0.15*
Panel 2B. Distance-to-default						
Low risk	-7.2%	-9.0%	-12.1%	-13.8%	-16.6%	-11.7%
Mid	-2.7%	-10.9%	-12.7%	-17.9%	-9.1%	-10.7%
High risk	-16.7%	-20.4%	-23.8%	-23.3%	-29.8%	-22.5%
High-Low	-10.2%	-12.5%	-13.3%	-10.9%	-15.8%	-12.2%
t (High-Low)	*-0.46*	*-0.88*	*-0.97*	*-0.92*	*-1.10*	*-0.86*
Panel 2C. Credit spread						
Low risk	-5.2%	-13.0%	-15.3%	-15.9%	-11.6%	-12.1%
Mid	-21.7%	-7.1%	-18.9%	-15.1%	-19.0%	-16.1%
High risk	-17.1%	-21.4%	-26.3%	-30.3%	-30.4%	-24.2%
High-Low	-12.6%	-9.6%	-13.0%	-17.1%	-21.2%	-13.8%
t (High-Low)	*-0.51*	*-0.69*	*-1.03*	*-1.66*	*-1.98*	*-1.15*
Panel 2D. Credit rating						
Low risk	-15.3%	-8.9%	-11.6%	-17.0%	-11.6%	-12.4%
Mid	-13.2%	-9.3%	-16.4%	-16.2%	-17.2%	-14.1%
High risk	-16.6%	-24.2%	-24.2%	-26.0%	-26.8%	-23.3%
High-Low	-1.6%	-16.8%	-14.3%	-10.9%	-17.2%	-12.5%
t (High-Low)	*-0.09*	*-1.20*	*-1.16*	*-1.05*	*-1.30*	*-1.04*

When we consider the portfolio returns during expansions and recessions in Panels 1 and 2 of Table 4.3, respectively, it appears that stock returns are highly positive on average during expansions and negative during contractions. This result clearly indicates that the NBER's Business Cycle indicators differentiate between good and bad states of the economy. When consider the return differential between value and growth stocks during expansions and recessions, it appears that value stocks outperform growth stocks during expansions, irrespective of which distress risk measure is used to construct the portfolios. The average return in expansions of value stocks with median distress risk compared to growth stocks with median distress risk ranges from 4.7 percent per annum in case distance-to-default (= 18.0 – 13.3 percent) and credit spread (= 18.1 – 13.4 percent) are used to construct the portfolios to 6.8 (19.6 – 12.8) percent in case debt-to-assets is used. Value stocks, however, also show a better performance than growth stocks during recessions. In fact, in three out of four cases (for sorts using debt-to assets, distance-to-default and credits ratings in Panels 2A, 2B and 2D, respectively) there is a large positive value premium during recessions. These results are in line with the findings of Lakonishok, Shleifer and Vishny (1994) and very difficult to reconcile with the risk-based explanation for the value premium that predicts the opposite.

At the same time, we do not observe a particular return pattern for stocks with different distress risk characteristics during expansions. High-risk stocks with a relatively high debt-to-assets ratio earn somewhat higher returns than stocks with a low debt-to-assets ratio, but for our other risk measures we do not observe such a pattern. Interestingly, we observe a clear return pattern for stocks with different levels of distress risk during economic recessions in Panel 2 of Table 4.3. When distance-to-default, credit spreads and ratings are used as risk measures, we see that the return differentials between high- and low-risk stocks are over 10 percent per annum. These results indicate that our risk measures capture some form of distress risk.

4.4.4. The value premium analyzed using Fama-MacBeth regressions

To investigate if the magnitude of the estimated value premium is affected by including stock exposures to distress risk in the regressions we use cross-sectional Fama-MacBeth regressions [see Fama and MacBeth (1973)] for individual stock returns. The primary attractive feature of Fama-MacBeth regressions compared to the rank portfolio approaches we employed in our previous analyses is that Fama-MacBeth regressions enable us to control for multiple other effects that might affect the relation between stock returns, valuation and distress risk. For example, in our earlier analyses we only control for size when investigating the relation between value and distress risk. This requires us to construct triple-sorted portfolios. It would not be feasible to correct for an additional factor and construct quadruple-sorted portfolios because the number of stocks ending up in the resulting portfolios would become too small. With the Fama-MacBeth regressions on the other hand, we can easily include multiple factors when estimating the value premium.

In our first analysis we monthly regress stock returns on book-to-price ratios while controlling for market beta, intermediate-term return momentum, short-term return reversal and industries:

$$(4.3)\; r_{i,t} = a_t + b1_t BM_{i,t} + b2_t MCAP_{i,t} + b3_t BETA_{i,t} + b4_t MOM_{i,t} + b5_t REV_{i,t} + \delta_t Z_i + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of stock i in month t, $BM_{i,t}$ is the normalized book-to-market ratio of stock i in month t, $MCAP_{i,t}$ is the normalized logarithm of the market capitalization of stock i in month t, $BETA_{i,t}$ is the normalized market beta of stock i in month t estimated using a three-year rolling window using weekly returns and the BMI index as proxy for the market return, $MOM_{i,t}$ is the normalized 11-month one-month lagged past return of stock i in month t, $REV_{i,t}$ is the normalized return of stock i over the past month in month t, and Z_i is a vector containing industry dummies for stock i based on the MSCI/S&P GICS level 1 classification of ten industries.[53] Our main reason to control for the short-term reversal effect is the recent finding of Da and Gao (2010) that the distress risk premium documented by Vassalou and Xing (2004) can largely be attributed to a short-term liquidity-induced price reversal caused by mutual funds decreasing their holdings of shares after firms experiencing sharp rises in their default likelihood measures. By controlling for short-term reversals, we can assure that we capture effects distinct from those documented by Da and Gao (2010).

We augment our base case regression in Equation 4.3 with the normalized probabilities of our four alternative proxies for distress risk and rerun the regressions. Table 4.4 presents the average coefficient estimates of the different regression models together with their *t*-values computed using Fama-MacBeth standard errors. In addition, the table shows the average adjusted R-squared values of the regressions.

When we consider the resulting coefficient estimates of our base case regression in column (1), we observe a substantial value premium: the coefficient estimate of 0.06 percent for BM indicates that stocks earn an additional return of 0.06 percent per month for a one-standard deviation increase in their book-to-price ratio. The large negative coefficient estimate for REV indicates a negative autocorrelation in stock returns. We find only weak evidence supporting an intermediate-term momentum effect in stock returns using the Fama-MacBeth regressions. Columns (2) to (5) of Table 4.4 show the coefficient estimates when we augment our base case regression model with our normalized measures of distress risk. If the value premium can be attributed to distress risk, we should observe that augmenting the cross-

[53] We normalize the explanatory variables in the Fama-MacBeth regressions by subtracting the cross-sectional median from each observation and by dividing this difference by the cross-sectional standard deviation of the observations in each month. In addition, we winsorize the resulting normalized variables by imposing a maximum of 3 and a minimum of -3.

TABLE 4.4. Fama-MacBeth regression results for the relation value effect and distress risk characteristics

This table reports Fama-MacBeth regression results of stock returns regressed on book-to-market ratios while controlling for market capitalization, market beta, intermediate-term return momentum, short-term return reversal and industries for the 1,500 largest U.S. stocks from September 1991 until December 2012. Each month the following regression is performed:

(4.3) $$r_{i,t} = a_t + b1_t BM_{i,t} + b2_t MCAP_{i,t} + b3_t BETA_{i,t} + b4_t MOM_{i,t} + b5_t REV_{i,t} + \delta_t Z_i + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of stock i in month t, $BM_{i,t}$ is the normalized book-to-market ratio of stock i in month t, $MCAP_{i,t}$ is the normalized logarithm of market capitalization of stock i in month t, $BETA_{i,t}$ is the normalized market beta of stock i in month t estimated using a three-year rolling window using weekly returns and the BMI index as proxy for the market return, $MOM_{i,t}$ is the normalized 11-month one-month lagged past return of stock i in month t, $REV_{i,t}$ is the normalized return of stock i over the past month in month t, and Z_i is a vector containing industry dummies for stock i based on the MSCI/S&P GICS level 1 classification of ten industries. The base case regression in Equation 4.3 is augmented with our four alternative proxies for distress risk. The table presents the average coefficient estimates of the different regression models together with their t-values computed using Fama-MacBeth standard errors. In addition, the table shows the average adjusted R-squared values of the regressions.

	(1)	(2)	(3)	(4)	(5)
Constant	1.02%	1.02%	1.02%	1.02%	1.02%
	3.40	3.40	3.40	3.40	3.39
BM	0.06%	0.06%	0.06%	0.06%	0.06%
	1.57	1.49	1.73	1.57	1.62
MCAP	-0.05%	-0.06%	-0.07%	-0.09%	-0.10%
	-1.14	-1.53	-1.75	-2.33	-2.38
BETA	-0.06%	-0.07%	-0.05%	-0.04%	-0.04%
	-0.73	-0.82	-0.69	-0.59	-0.52
MOM	0.09%	0.09%	0.08%	0.09%	0.10%
	1.21	1.22	1.17	1.19	1.34
REV	-0.12%	-0.12%	-0.13%	-0.13%	-0.12%
	-2.42	-2.37	-2.69	-2.55	-2.48
Z	yes	yes	yes	yes	yes
Debt-to-assets		-0.05%			
		-1.41			
Distance-to-default			-0.04%		
			-0.97		
Credit spread				-0.08%	
				-1.65	
Credit rating					-0.09%
					-2.06
Adj. R2	8.20%	8.63%	8.60%	8.61%	8.63%

sectional regressions of stock returns on book-to-price ratios with our measures of distress risk should lead to a significant decrease of the estimated value premium. At the same time the measures for distress risk should encompass the explanatory power of stocks' book-to-price ratios and their coefficient estimates should become positive and significant. However, in all cases we observe that the coefficient estimate for BM remains nearly unchanged. Moreover, none of the coefficient estimates for our distress risk measures turns out significantly positive. Consistent with Anginer and Yıldızhan (2017) we find an insignificant negative relation between stock returns and credit spread. In fact, for all our measures of distress risk we observe a negative coefficient estimate for distress risk. These results are consistent with our earlier findings that there is no distress risk premium and that the value anomaly cannot be attributed to distress risk.

Overall, the results of our Fama-MacBeth regression analysis are consistent with our results based on rank portfolios and conditional time series analyses. It appears that the results we documented in the previous sections are not affected by market beta, momentum, reversal and industry effects and that our finding that the value premium is unrelated to distress risk is robust to the method that is used to investigate the relation between the two variables.

4.5. The size premium and distress risk

Just like for the value premium, it seems that the literature is not conclusive about the explanations for the existence of the size anomaly. On the one hand, a strand of literature attributes the size effect to a common risk factor. Chan, Chen and Hsieh (1985), Chan and Chen (1991), Petkova (2006), and Hwang, Min, McDonald, Kim, and Kim (2010) examine the correlation between the return differential between small- and large-cap stocks and several risk factors over time. Chan, Chen and Hsieh (1985) find evidence that the default spread and other factors that are related to changes in the economic environment are positively related to the small-cap premium. Chan and Chen (1991) find that small-cap portfolios contain a disproportional large amount of marginal firms with low production efficiency and high financial leverage. Petkova (2006), and Hwang, Min, McDonald, Kim, and Kim (2010) find that the SMB (Small-Minus-Big) factor of Fama and French (1993) is positively correlated with innovations in variables that describe investment opportunities, such as the default spread. And Vassalou and Xing (2004) employ a cross-sectional approach to investigate the relation between size and distress risk and show that the small-cap premium is fully concentrated in high-risk stocks. On the other hand, there are also several papers that argue that the size effect is unrelated to risk [see, e.g., Daniel and Titman (1997), Knez and Ready (1997), Ferson, Sarkissian and Simin (1999), Berk (2000)].

In this section we employ the framework used earlier to investigate the relation between distress risk and the value premium, to test if there is empirical evidence supporting a distress risk-based explanation of the small-cap effect.

4.5.1. The small-cap premium and distress risk

We start our analysis by investigating the size effect in our sample of the largest 1,500 U.S. stocks by monthly ranking the stocks on their market capitalization, sorting them into quintile portfolios and computing the equally-weighted returns over the subsequent month. Our results show that the 20 percent smallest stocks outperform the 20 percent largest stocks with an insignificant 1.7 percent per annum over the period September 1991 to December 2012. Consistent with evidence in the academic literature, the size premium is of significant smaller magnitude than the value premium we found in our sample of 5.3 percent per annum. In fact, several studies even suggest that the size effect disappeared after the early 1980s [e.g. Eleswarapu and Reinganum (1993), Chan, Karceski, and Lakonishok (2000), Horowitz, Loughran and Savin (2000), and Hirshleifer (2001)].

To investigate if the higher returns of small-cap stocks are indeed concentrated in stocks with high distress risk, we construct portfolios of stocks ranked on their market capitalization and each of our four measures of distress risk. Since high-risk stocks typically have a smaller market capitalization than low-risk stocks, we form triple-sorted portfolios of stocks to ensure that the market capitalizations of the high- and low-risk portfolios are in the same order of magnitude and that any return differences between portfolios in the same size segment cannot be attributed to differences in market capitalization. More specifically, every month we sort stocks into quintile portfolios based on their market capitalization. Then, within each size portfolio we further sort stocks into terciles based on their market capitalization. Then, for each size sub-portfolio we sort stocks into terciles based on their debt-to-assets ratio, distance-to-default, credit spread and credit rating. Finally, we merge the small-, mid- and large-cap sub-portfolios of high-risk stocks within each size quintile portfolio. We also merge the three market cap sub-portfolios of mid- and low-risk stocks within each size sub-portfolio. We compute the equally-weighted returns over the subsequent month for the resulting 15 portfolios, as well as the portfolios’ median distress risk characteristics. The results are listed in Table 4.5.

TABLE 4.5. Size effect controlled by distress risk
This table reports annualized returns of triple-sorted portfolios of stocks ranked on their market capitalization and each of our four measures of distress risk for the 1,500 largest U.S. stocks from September 1991 until December 2012. Each month, stocks are sorted into quintiles based on their market capitalization. Then, for each size portfolio, stocks are further sorted into terciles based on their market capitalization. Then, for each size sub-portfolio stocks are sorted into terciles based on their debt-to-assets ratio, distance-to-default, credit spread or credit rating. Finally, the small-, mid- and large-cap portfolios with similar risk are merged. Portfolio returns are computed by weighting equally the firms.

	Small	2	3	4	Large	All
Panel A. Debt-to-assets						
Low risk	8.8%	6.1%	8.8%	11.6%	9.3%	9.0%
Mid	11.4%	11.8%	11.7%	11.4%	9.3%	11.2%
High risk	10.9%	12.6%	10.0%	9.3%	8.8%	10.6%
High-Low	1.9%	6.1%	1.1%	-2.0%	-0.5%	1.5%
t (High-Low)	*0.53*	*1.72*	*0.36*	*-0.70*	*-0.16*	*0.49*
Panel B. Distance-to-default						
Low risk	13.8%	10.2%	11.4%	11.4%	10.1%	11.6%
Mid	13.1%	12.7%	12.4%	12.6%	9.5%	11.8%
High risk	9.0%	12.0%	8.1%	9.0%	7.2%	9.4%
High-Low	-4.2%	1.6%	-3.0%	-2.2%	-2.6%	-2.0%
t (High-Low)	*-1.46*	*0.59*	*-1.07*	*-0.83*	*-1.16*	*-0.82*
Panel C. Credit spread						
Low risk	14.3%	13.9%	14.1%	11.9%	8.7%	12.1%
Mid	14.2%	13.7%	11.0%	12.1%	8.9%	12.1%
High risk	7.4%	8.5%	8.5%	11.1%	7.8%	9.6%
High-Low	-6.0%	-4.7%	-4.9%	-0.7%	-0.8%	-2.3%
t (High-Low)	*-1.61*	*-1.65*	*-1.90*	*-0.28*	*-0.37*	*-0.96*
Panel D. Credit rating						
Low risk	15.5%	12.5%	12.8%	12.2%	10.0%	12.5%
Mid	13.4%	14.9%	11.1%	12.7%	10.5%	12.5%
High risk	11.6%	6.9%	10.6%	7.8%	8.2%	9.7%
High-Low	-3.3%	-5.0%	-2.0%	-4.0%	-1.7%	-2.5%
t (High-Low)	*-0.93*	*-1.69*	*-0.68*	*-1.58*	*-0.70*	*-1.02*

When we consider the portfolio's returns in Table 4.5 we indeed observe a size effect in the sense that the small-cap portfolios earn higher returns than the large-cap portfolios. If small-cap stocks earn higher returns because they have more distress risk, we should observe a positive relation between default risk and returns of small-cap stocks.

However, for three out of our four distress risk measures, we do not observe that the high returns of small-cap stocks are concentrated in the high-default-risk segment. In fact, when distance-to-default, credit spread and credit rating are used as measures for distress risk, it appears that high-risk small-cap stocks earn up to 6.0 percent lower returns than low-risk small-cap stocks. Additionally, if the small-cap premium is a compensation for distress risk, large-cap stocks earn lower returns because they have less distress risk and we should also observe a positive relation between default risk and returns of large-cap stocks. Conversely, we find that for all four distress risk measures the low returns of large-cap stocks are concentrated in the high-default-risk segment. Therefore, it seems unlikely that distress-risk drives the small-cap premium.

4.5.2. The small-cap premium and distress risk during bad states of the world

We also evaluate the performance differential between small- and large-cap stocks over different states of the business cycle. If small-cap stocks run more distress risk than large-cap stocks, they must underperform large-cap stocks in the bad states of the world. As with our business cycle analysis in the previous section, we take the NBER's Business Cycle indicators for economic expansions and recessions and evaluate the relation between distress risk and equity returns for our triple-sorted portfolios on market capitalization and distress risk. For all portfolios we compute their returns during expansions and recessions.

For the sake of brevity these results are not presented in tabular form. When we consider the portfolio returns during expansions and recessions it appears that stock returns are highly positive on average during expansions and negative during recessions. Using distance-to-default, credit spread and credit ratings as measures for distress risk, we observe that high-risk stocks earn lower returns than low-risk stocks during recessions with return differentials between high- and low-risk stocks of more than 10 percent per annum. At the same time, however, it appears that small-cap stocks do not only outperform large-cap stocks during expansions, but also during recessions. In fact, for three out of the four different risk measures we find a large positive size effect during recessions. These results corroborate our earlier result that it seems unlikely that the size effect can be attributed to distress risk.

4.5.3. The small-cap premium analyzed using Fama-MacBeth regressions

Finally, we turn back to our regression results in the previous section to analyze the relation between the size effect and distress risk using cross-sectional Fama-MacBeth regressions. If a portion of the size effect is related to distress risk, we should observe that the coefficient estimate for *MCAP* of Table 4.4 should become less significant once the regression model is augmented with our distress risk variables. However, in all four cases it appears that the coefficient estimate for *MCAP* becomes more negative once our distress risk variables are added to the model. In fact, we find an insignificant size premium which becomes significant once distress risk is included in the regression. These results indicate that small-cap stocks with high distress risk earn lower returns than small-cap stocks with a more healthy financial status and are again inconsistent with the notion that small-cap stocks earns higher returns because of increased distress risk.

It is also noteworthy to mention here that our results might help to understand why several studies do not find a significant size premium after the early 1980s: apparently, over the past decades the size effect has been concentrated in low-distress risk stocks, and if this interaction is not taken into account in the analyses, the high-risk discount may effectively offset the small-cap premium. We contribute to this stream of literature by showing that the small-cap premium is present after the early 1980s once distress risk is taken into account in the analyses.

4.6. The Fama-French (1993) SMB and HML factors and distress risk

The typical approach in the stream of literature on empirical asset pricing to correct for the size and value effects is using the Fama-French (1993) three factor model that augments the one-factor market model with the SMB (Small-Minus-Big) and HML (High-Minus-Low) factors. Perhaps the most important reason why many researchers adopted the use of the SMB and HML factors is because of the factors' large empirical explanatory power for differences in the cross-section of stock returns. Because of the way the SMB and HML factors are constructed, we may expect the factors to be prone to distress risk (we refer to the webpage of Kenneth French for a detailed documentation on the construction of the SMB and HML factors and to the recent work of Cremers, Petajisto, and Zitzewitz (2011) for an in-depth analysis of the impact of small-cap stocks on the returns of the SMB and HML factors).

In this section we investigate if the large empirical explanatory power of the Fama-French (1993) factors can be attributed to these factors being exposed to distress risk. More specifically, we investigate if the empirical explanatory power of the SMB and HML factors is negatively affected when distress-risk neutrality is imposed when the factors are constructed.

To conduct our analysis we use the decile portfolios sorted on dividend yield and the 5x5 double-sorted portfolios on market capitalization and book-to-price from the webpage of Kenneth French as test assets. Pricing errors are estimated using the three-factor Fama-French model

$$(4.4)\quad r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + \varepsilon_{i,t}\,.$$

In these equations, $r_{i,t}$ is the return of portfolio *i* at time *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for market, size, and value, respectively, at time *t*. Return data for the risk-free rate and the market factor are from the webpage of Kenneth French. We construct the SMB and HML factors using our sample covering the 1,500 largest stocks of the Citigroup US Broad Market Index (BMI) over the period September 1991 until December 2012 and the methodology as outlined on the webpage of Kenneth French. More specifically, following Fama and French (1993) we first construct six value-weighted portfolios on market capitalization and book-to-price. These portfolios, which are constructed at the end of each month, are the intersections of two portfolios formed on market capitalization, and three portfolios formed on book-to-price. The size breakpoint for month *t* is the median market capitalization at the end of month *t*. The book-to-price for month *t* is the book equity for the most recent fiscal quarter divided by market capitalization at the end of month *t*. The book-to-price breakpoints are the 33th and 66th percentiles for month *t*. SMB is the average value-weighted return on the three small portfolios minus the average value-weighted return on the three big portfolios,

$$(4.5)\quad \begin{aligned} &\text{SMB} = 1/3\ (\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) \\ &-1/3\ (\text{Big Value} + \text{Big Neutral} + \text{Big Growth}) \end{aligned}$$

and HML is the average value-weighted return on the two value portfolios minus the average value-weighted return on the two growth portfolios,

$$(4.6)\quad \text{HML} = 1/2\ (\text{Small Value} + \text{Big Value}) - 1/2\ (\text{Small Growth} + \text{Big Growth})\ .$$

Additionally, we construct return series for SMB and HML imposing distress-risk neutrality. To impose distress-risk neutrality we perform a triple sort where we first sort stocks into distress risk terciles and next perform the double sort on market capitalization and book-to-price as outlined above. The six base portfolios that are used to construct the SMB and HML factors are now the average value-weighted return series for the distress risk terciles. For example, Small Value is now the average of the return series for the Low Risk/Small Value, Mid Risk/Small Value, and High Risk/Small Value portfolios. And Big

TABLE 4.6. Summary statistics and correlations of SMB and HML distress-risk neutral factors

This table presents return and risk characteristics of the market factor and of the SMB and HML factor with and without distress risk neutrality imposed for each of our four measures of distress risk (Panel A). The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2012 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. Panel B shows the correlations between factors.

	RMRF	SMB	SMB Debt-to-assets	SMB Distance-to-default	SMB Credit spread	SMB Credit rating	HML	HML Debt-to-assets	HML Distance-to-default	HML Credit spread	HML Credit rating
Panel A. Summary statistics											
Return (annualized)	5.52%	2.17%	1.61%	2.56%	3.07%	3.52%	2.29%	2.16%	2.71%	1.16%	2.48%
Volatility (annualized)	15.36%	8.43%	8.81%	6.87%	6.21%	7.46%	14.03%	11.31%	10.34%	10.12%	10.15%
Sharpe ratio	0.36	0.26	0.18	0.37	0.49	0.47	0.16	0.19	0.26	0.11	0.24
5th Percentile	-7.68%	-3.75%	-3.62%	-2.52%	-2.26%	-2.86%	-4.94%	-4.95%	-4.37%	-4.66%	-4.05%
25th Percentile	-1.98%	-1.48%	-1.47%	-1.00%	-0.83%	-0.92%	-1.48%	-1.07%	-0.85%	-1.08%	-1.22%
Debt-to-assets		-0.03	0.00	-0.04	0.04	0.03	0.12	0.00	0.02	-0.02	-0.01
Distance-to-default		-2.1	-2.1	-0.2	-1.0	-1.0	-2.0	-1.9	-0.6	-1.2	-1.5
Credit spread		159	169	94	32	56	-3	-20	-14	10	27
Credit rating (top / bottom)		BB+ / BBB+	BB+ / BBB+	BBB- / BBB+	BBB / BBB+	BBB / BBB	BBB / BBB-	BBB / BBB-	BBB / BBB-	BBB+ / BBB	BBB / BBB
Panel B. Correlations											
RMRF	1.00										
SMB	0.29	1.00									
SMB Debt-to-assets neutral	0.37	0.97	1.00								
SMB Distance-to-default neutral	0.09	0.83	0.86	1.00							
SMB Credit spread neutral	-0.27	0.49	0.47	0.71	1.00						
SMB Credit rating neutral	-0.12	0.46	0.48	0.73	0.76	1.00					
HML	-0.05	-0.13	-0.05	0.17	0.27	0.58	1.00				
HML Debt-to-assets neutral	0.03	-0.01	0.04	0.17	0.23	0.50	0.93	1.00			
HML Distance-to-default neutral	-0.18	-0.16	-0.13	0.10	0.30	0.54	0.92	0.90	1.00		
HML Credit spread neutral	0.06	0.00	0.08	0.24	0.24	0.57	0.85	0.79	0.77	1.00	
HML Credit rating neutral	0.07	0.03	0.10	0.25	0.25	0.60	0.90	0.87	0.84	0.92	1.00

Growth, for example, is the average of the return series for the Low Risk/Big Growth, Mid Risk/Big Growth, and High Risk/Big Growth portfolios. The distress risk breakpoints are the 33th and 66th percentiles for month *t*. We construct distress-risk neutral SMB and HML factors using our four measures for distress risk.

Before testing the empirical explanatory power of the SMB and HML factors with and without distress-risk neutrality imposed, we first consider the summary statistics and investigate the distress risk exposures of the SMB and HML factors, the differential premiums after neutralization, the factors' risks, and their correlations. Panel A of Table 4.6 shows the summary risk and return statistics of the market factor and the SMB and HML factors with and without distress-risk neutrality imposed. When we consider the last four rows in Panel A, we observe that the SMB factor is exposed to distress risk as the negative distance-to-default and the credit spread of 159 basis points indicate that small caps are more exposed to distress risk than large caps. Also the BB+ rating for small caps is worse than the BBB+ rating for large caps. Only based on debt-to-assets small caps do not seem to be more risky than large caps. These findings are consistent with our earlier results. When we consider the exposures of the HML factor, we observe that the factor is only marginally exposed to distress risk as the credit spreads and credit ratings are almost equal for stocks with a high and low book-to-market ratio. Only based on debt-to-assets ratios and the distance-to-default measure we observe that value stocks are more risky than growth stocks. These results already indicate that it is unlikely that the HML factor picks up distress risk and the factor's explanatory power is driven by distress risk exposure. Furthermore, we observe that the distress-risk neutral SMB and HML factors are, by construction, generally less exposed to distress risk than the standard SMB and HML factors. The distress-risk neutral SMB factors have distances-to-default and credit spreads closer to zero and a smaller difference in credit rating between small and large caps. And also the distress-risk neutral HML factor has distances-to-default closer to zero.

Interestingly, we observe that the premiums of the SMB and HML factor are still present when distress-risk neutrality is imposed. The risk premiums of the SMB and HML distress-risk neutral factors range from 1.61 to 3.52 percent and from 1.16 to 2.71 percent per annum, respectively, compared to a 2.17 percent SMB premium and a 2.29 percent HML premium without neutrality being imposed. When we consider the risks of the factors, we find in almost all cases that the distress-risk neutral factors exhibit substantially lower levels of risk as measured by lower return standard deviations and lower extreme negative returns (i.e., 5th and 25th percentile returns). The same return levels together with the lower risk levels result in higher Sharpe ratios for most of our distress-risk neutral factors. These results indicate that distress risk is not driving the premiums of the SMB and HML factors. We additionally estimate correlations between the return series which are presented in Panel B of Table 4.6. Correlations between the Fama and French SMB factor and the distress-risk neutral SMB factors range between 0.46 and 0.97. For the Fama and French HML factor the correlations range between 0.85 and 0.93. Although the correlations are high as expected, the results indicate that the regressions in Equation 4.4 might result in different outcomes. This raises the question which factors are better able to explain the variability in returns of our test assets.

To assess the empirical explanatory power of the alternative SMB and HML factors we estimate pricing errors for the CAPM and the Fama-French (1993) three-factor model using the SMB and HML factors with and without distress-risk neutrality. We consider average and median pricing errors and adjusted R-squared values of the regressions to measure the descriptive power of the factors. In addition, we compute the Gibbons-Ross-Shanken (1989) statistic as:

$$(4.7)\quad \mathrm{GRS} \equiv \left(\frac{\mathrm{T\text{-}N\text{-}K}}{N}\right)\left(1+\hat{\mu}'\hat{\Omega}^{-1}\hat{\mu}\right)^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \sim F\left(N, T-N-K\right)$$

where T is the number of observations in the time series, N is the number of test asset portfolios (thus 10 in case of the decile portfolios sorted on dividend yield and 25 in case of the 5x5 double-sorted portfolios on market capitalization and book-to-price), K is the number of factors that we use in the factor model (thus K = 1 for the CAPM and K = 3 for the Fama-French (1993) three-factor model), $\hat{\alpha}$ is a N by 1 vector of estimated alphas, $\hat{\Sigma}$ is an N by N matrix that holds the unbiased estimate of the residual variance-covariance matrix, $\hat{\mu}$ is a K by 1 vector of sample means of the test asset portfolios' excess returns, and $\hat{\Omega}$ is a K by K matrix that holds the unbiased estimate of the test asset portfolios’ covariance matrix. Assuming that the residuals are independently and normally distributed, and uncorrelated with the returns on the model’s factors, the GRS statistic follows a F-distribution with N degrees of freedom in the numerator and T-N-K degrees in the denominator under the null of zero alphas. Apart from the GRS statistic, we also compute the following test statistic to find out if all alphas are jointly equal to zero:

$$(4.8)\quad T\left(1+\hat{\mu}'\hat{\Omega}^{-1}\hat{\mu}\right)^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \sim \chi^2_N$$

This test statistic does not require normality of the error terms. Assuming homoscedasticity this test statistic obeys an asymptotic χ^2 -distribution with N degrees of freedom under the null of zero alphas. The results for the decile portfolios sorted on dividend yield are presented in Table 4.7. For each of the 10 portfolios, the table presents annualized returns, annualized constants (a) and associated t-values, and the adjusted R-squared values of the different regression models. In addition, the table shows the average and median pricing errors of the models for the 10 portfolios based on the absolute values of the constants and t-values and their GRS and χ^2 test statistics.

If distress risk is effective in explaining cross-sectional return differences, then neutralizing this risk in the SMB and HML factors should lead to an increase in pricing errors. However, we observe that in most cases the average and median pricing errors become smaller when distress risk neutrality is imposed indicating that distress risk-exposure is not the driving force behind the large empirical explanatory power of the SMB and HML factors. In fact, irrespective of which distress-risk neutral factors are used in the three-factor model, in all cases we observe an improvement in both the GRS and chi-squared test statistics when it comes to explaining the test asset portfolios' returns. These findings have significant implications for the stream of literature that attributes a large portion of the explanatory power of the Fama-French factors to distress risk.

The results for the 5x5 double-sorted portfolios on market capitalization and book-to-price are presented in Table 4.8. For the sake of brevity Table 4.8 only shows the average and median pricing errors of the models for the 25 portfolios based on the absolute values of the constants and t-values and their GRS and χ^2 test statistics. When we consider the empirical explanatory power of the three-factor Fama-French model, we observe an average adjusted R-squared value of 86 percent and average and median pricing errors of 1.85 and 1.22 percent, respectively. The GRS and chi-squared test statistics indicate that the null hypothesis of zero alphas is clearly rejected.

If the large empirical explanatory power of the Fama-French (1993) factors can be attributed to the factors being exposed to distress risk we should observe an increase in pricing error when the returns of the test assets are evaluated using the SMB and HML factors that are constructed imposing distress-risk neutrality. However, we do not observe deterioration in explaining the variation in returns of the 25 portfolios. In fact, in three out

TABLE 4.7. Pricing errors for decile portfolios sorted on dividend yield

This table reports regression results of the decile portfolios sorted on dividend yield from the webpage of Kenneth French on the three-factor Fama-French model

(4.4) $r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + +\varepsilon_{i,t}$,

where $r_{i,t}$ is the return of portfolio *i* at time *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for market, size, and value, respectively, at time *t*. The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2012 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. The table reports the average annualized returns, regression intercepts and their associated t-value and adjusted R-squared values. In addition, the table reports average and median absolute intercepts, t-values (pricing errors), and adjusted R-squared values, and GRS and chi-squared test statistics.

		Fama-French			Fama-French risk-neutral (Debt-to-assets)			Fama-French risk-neutral (Distance-to-default)			Fama-French risk-neutral (Credit spread)			Fama-French risk-neutral (Credit rating)		
	Return	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2
Low DY	5.21%	-2.31%	-1.33	85%	-2.46%	-1.41	85%	-2.09%	-1.22	85%	-2.24%	-1.29	85%	-1.79%	-1.05	85%
DY2	6.27%	-0.65%	-0.41	84%	-0.61%	-0.39	84%	-0.61%	-0.38	84%	-1.02%	-0.61	84%	-0.36%	-0.22	84%
DY3	6.69%	-0.26%	-0.17	81%	-0.27%	-0.18	80%	-0.65%	-0.45	79%	-0.33%	-0.22	79%	-0.61%	-0.41	79%
DY4	8.49%	2.68%	1.73	76%	2.79%	1.65	75%	2.11%	1.41	75%	1.70%	1.09	76%	1.73%	1.19	76%
DY5	6.86%	0.28%	0.17	75%	0.44%	0.22	71%	-0.45%	-0.24	72%	-0.46%	-0.23	72%	-0.49%	-0.27	72%
DY6	6.62%	1.29%	0.80	77%	1.24%	0.71	73%	0.80%	0.50	73%	1.38%	0.84	67%	1.07%	0.68	69%
DY7	7.63%	1.35%	0.93	82%	1.43%	0.81	78%	0.66%	0.40	78%	1.35%	0.79	74%	1.02%	0.62	75%
DY8	8.62%	2.55%	1.93	82%	2.72%	1.59	76%	1.66%	1.08	77%	2.67%	1.65	74%	2.33%	1.41	75%
DY9	8.67%	2.84%	1.53	73%	3.02%	1.44	68%	1.64%	0.88	73%	3.45%	1.87	69%	2.37%	1.23	71%
High DY	6.92%	0.34%	0.10	56%	0.93%	0.26	49%	-1.08%	-0.30	53%	0.69%	0.21	57%	-0.69%	-0.19	58%
Average abs pricing error		1.45%	0.91	77%	1.59%	0.87	74%	1.18%	0.69	75%	1.53%	0.88	74%	1.25%	0.73	74%
Median abs pricing error		1.32%	0.86	79%	1.34%	0.76	75%	0.94%	0.47	76%	1.37%	0.82	74%	1.05%	0.65	75%
GRS test stat (p-value)		GRS = 0.93 (0.50)			GRS =0.88 (0.56)			GRS = 0.67 (0.75)			GRS = 0.70 (0.72)			GRS = 0.66 (0.76)		
X^2 test stats (p-value)		X^2 = 9.84 (0.45)			X^2 = 9.23 (0.51)			X^2 = 7.10 (0.72)			X^2 = 7.43 (0.68)			X^2 = 6.97 (0.73)		

TABLE 4.8. Pricing errors for 5x5 portfolios sorted on size and value

This table reports regression results of the 5x5 double-sorted portfolios on market capitalization and book-to-price from the webpage of Kenneth French on the three-factor Fama-French model

(4.4) $r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + +\varepsilon_{i,t}$,

where $r_{i,t}$ is the return of portfolio i at time t in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for market, size, and value, respectively, at time t. The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2012 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. The table reports average and median absolute intercepts of the 25 portfolios, average t-values (pricing errors) and adjusted R-squared values, and GRS and chi-squared test statistics.

	Fama-French			Fama-French risk-neutral (Debt-to-assets)			Fama-French risk-neutral (Distance-to-default)			Fama-French risk-neutral (Credit spread)			Fama-French risk-neutral (Credit rating)		
	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2
Average abs pricing error	1.85%	1.12	74%	2.27%	1.25	73%	1.63%	0.86	72%	1.61%	0.71	67%	1.51%	0.70	68%
Median abs pricing error	1.22%	0.97	84%	1.61%	1.10	84%	1.32%	0.83	82%	0.73%	0.42	79%	1.06%	0.49	80%
GRS test stat (p-value)	GRS = 3.86 (0.00)			GRS = 4.11 (0.00)			GRS = 4.38 (0.00)			GRS = 3.63 (0.00)			GRS = 3.64 (0.00)		
X^2 test stats (p-value)	X^2 = 108.55 (0.00)			X^2 = 115.39 (0.00)			X^2 = 123.12 (0.00)			X^2 = 102.05 (0.00)			X^2 = 102.25 (0.00)		

of four cases the average pricing errors decrease when imposing distress risk neutrality. And in all four cases the median absolute pricing error decreases. More specifically, the average (median) pricing error of the Fama-French model is 1.85 (1.22) percent and ranges between 1.51 (0.73) percent and 2.27 (1.61) percent for the risk-neutral models. In addition, we do not observe that the GRS and chi-squared test statistics become substantially higher. In fact, for the SMB and HML factors that are neutral on credit spread and rating we even observe more favourable test statistics. These results corroborate our previous finding that it is not necessary to be exposed to distress-risk to be able to explain the differences in returns of the 25 Fama-French portfolios.

4.7. Results using the CRSP stock database over the pre-1991 period

Because (almost) no reliable data are available on credit spreads and ratings before 1991, the main results of our study are based on the post-1991 period. To investigate if our main result that the value and size premiums are unrelated to distress risk is robust over the pre-1991 period, we perform out-of-sample analyses using a subset of the distress risk measures we have used in the study.

More specifically, for our pre-1991 analyses we measure distress risk through firms' debt-to-assets and distance-to-default measures. Data on firms' book values on debt and equity are obtained from the Compustat database. Since Compustat data are available as from 1963, we can perform our out-of-sample analysis over the January 1963 to August 1991 period. (Our main analyses using credit rating and spread data documented in the previous sections start in September 1991). Our stock return data are obtained from the monthly CRSP Stock database. We select common U.S. stocks listed on the NYSE, AMEX and Nasdaq markets that have a market capitalization above the NYSE median and a stock price above \$5. We exclude closed-end funds, Real Estate Investment Trusts (REITs), unit trusts, American Depository Receipts (ADRs), and foreign stocks from our analysis. Similar to our previous analyses we sort stocks into tercile portfolios based on their measures of distress risk and then subdivide each tercile into quintiles based on the stocks' book-to-price ratios and compute equal-weighted returns. The results of the analysis are presented in Panel 1 of Table 4.9.

Consistent with our earlier analyses we find no evidence supporting a distress-risk-based explanation of the value premium. It does not seem to be the case that high-risk stocks earn higher returns than low-risk stocks for this analysis. We do observe that high-risk value stocks seem to earn positive excess returns, but the patterns is not consistent: low-risk growth

TABLE 4.9. Results using the CRSP stocks database over the pre-1991 period
This table reports statistics of double-sorted portfolios of stocks ranked on their book-to-market ratios, market capitalization, and distress risk for all common U.S. stocks listed on the NYSE, AMEX and Nasdaq markets that have a market capitalization above the NYSE median and a stock price above $5 over the January 1963 to August 1991 period. We exclude closed-end funds, Real Estate Investment Trusts (REITs), unit trusts, American Depository Receipts (ADRs), and foreign stocks from our analysis. Each month, stocks are sorted into terciles based on their distress risk as measured by debt-to-assets ratio and distance-to-default. Next, for each tercile portfolio stocks are further sorted into quintiles based on their book-to-market ratio (B/M) or market capitalization. Portfolio returns are computed by weighting equally the firms. Panel 1 reports the results for double sorts using book-to-market ratio and Panel 2 reports the results for double sorts using market capitalization.

	High/Small	2	3	4	Low/Large	All
Panel 1. Sorts on book-to-price ratios						
Panel 1A. Debt-to-assets						
Low risk	13.9%	13.1%	12.3%	12.8%	10.9%	12.6%
Mid	16.8%	15.2%	14.0%	11.2%	10.1%	13.4%
High risk	17.2%	12.7%	10.6%	10.1%	8.5%	11.8%
High-Low	3.3%	-0.3%	-1.6%	-2.7%	-2.4%	-0.8%
Panel 1B. Distance-to-default						
Low risk	15.1%	12.9%	12.0%	13.7%	12.2%	13.2%
Mid	14.5%	11.6%	12.1%	11.5%	9.2%	11.8%
High risk	17.6%	16.4%	13.1%	12.0%	9.9%	13.8%
High-Low	2.6%	3.5%	1.1%	-1.7%	-2.3%	0.6%
Panel 2. Sorts on market capitalization						
Panel 2A. Debt-to-assets						
Low risk	13.7%	14.0%	11.9%	12.8%	11.3%	12.7%
Mid	15.6%	14.8%	14.1%	12.9%	11.3%	13.7%
High risk	13.3%	12.5%	14.2%	11.7%	9.6%	12.3%
High-Low	-0.4%	-1.6%	2.3%	-1.1%	-1.6%	-0.5%
Panel 2B. Distance-to-default						
Low risk	15.3%	14.1%	13.2%	12.8%	11.6%	13.4%
Mid	14.0%	13.5%	12.7%	10.5%	10.2%	12.2%
High risk	15.7%	14.8%	15.3%	14.1%	10.1%	14.0%
High-Low	0.4%	0.7%	2.1%	1.3%	-1.5%	0.6%

stocks do not earn negative excess returns. Our results for the pre-1991 sample period thus corroborate our previous findings.

Proceeding further, we investigate the pre-1991 relationship between the small-cap premium and distress risk. Again we sort stocks into tercile portfolios based on their measures of distress risk and then subdivide each tercile into quintiles based on the stocks' market capitalizations and compute equal-weighted returns. The results of this analysis are presented in Panel 2 of Table 4.9. Also this analysis yields consistent results: it does not appear to be the case that the higher returns for small-cap stocks are concentrated in the high-risk segment of the market. For sorts on debt-to-assets we even find that the return of the low-risk small-cap portfolio is higher than the return of the high-risk small-cap portfolio. So also for our pre-1991 sample period we find that it is unlikely that the size premium can be attributed to distress risk.

Finally, we perform a pre-1991 robustness test for our analysis of the value premium conditional on the state of the economy. To this end we compute the return on the Fama-French HML factor during NBER expansions and recessions. The data for this analysis are available as of July 1926. When we perform the analysis we find that the results corroborate our previous finding that value stocks outperform growth stocks particularly during recessions: during expansions we observe an annualized return of 5.5 percent, while we observe a return of 2.7 percent during recessions. We therefore conclude that the results of our analysis of the value premium conditional on the state of the economy are also robust to an extended sample period.

4.8. International results

In this section we investigate the relation between the value and size premiums and distress risk in an international context. For our analysis we use data on the stocks in the FTSE World index, which are on average 1,870 stocks from developed market countries over our sample period from September 1991 until December 2012.

We start by investigating the value premium from an international perspective. Again, we observe a large value premium of 5.2 percent per annum, which is similar in size compared to the value premium we have documented for US stocks. We next analyze the relation between distress risk and returns for size-neutral distress risk portfolios. The results are presented in Table 4.10, Panel 1. We observe a negative relation between distress risk and return for all our measures of distress risk, as the returns of high-minus-low-risk stocks range between -0.8 percent when distance-to-default is used as a measure for distress risk up to -2.6 percent for the credit rating measure. Consistent with our US results we find a

TABLE 4.10. International results
This table reports statistics of triple-sorted portfolios of stocks ranked on their book-to-market ratios, market capitalization, and distress risk for the constituents of the FTSE World index over the period September 1991 until December 2012. Portfolio returns are computed by weighting equally the firms. Presented returns are annualized.

	High B/M	2	3	4	Low B/M	All
Panel 1. Sorts on book-to-price ratios						
Panel 1A. Debt-to-assets						
Low risk	12.0%	8.1%	7.0%	6.9%	7.5%	8.5%
Mid	14.4%	8.6%	7.9%	7.4%	6.8%	9.1%
High risk	11.2%	8.8%	5.7%	5.5%	4.7%	7.4%
High-Low	-0.7%	0.6%	-1.2%	-1.3%	-2.6%	-1.0%
t (High-Low)	*-0.32*	*0.37*	*-0.72*	*-0.73*	*-1.24*	*-0.72*
Panel 1B. Distance-to-default						
Low risk	9.3%	8.2%	7.6%	9.0%	9.2%	8.8%
Mid	12.4%	8.1%	8.2%	6.1%	5.4%	8.1%
High risk	14.6%	10.4%	6.0%	4.8%	2.9%	7.9%
High-Low	4.8%	2.0%	-1.5%	-3.9%	-5.8%	-0.8%
t (High-Low)	*1.20*	*0.78*	*-0.68*	*-1.68*	*-2.20*	*-0.32*
Panel 1C. Credit spread						
Low risk	14.2%	12.4%	9.5%	10.0%	9.3%	11.2%
Mid	12.2%	11.8%	10.0%	10.2%	10.5%	11.1%
High risk	7.7%	10.0%	7.3%	9.2%	8.9%	9.1%
High-Low	-5.7%	-2.1%	-2.0%	-0.7%	-0.4%	-1.9%
t (High-Low)	*-1.45*	*-0.86*	*-0.96*	*-0.37*	*-0.15*	*-0.96*
Panel 1D. Credit rating						
Low risk	13.3%	12.9%	12.8%	10.2%	10.2%	12.1%
Mid	13.8%	15.6%	10.5%	12.1%	9.7%	12.6%
High risk	12.2%	9.4%	6.9%	8.4%	7.6%	9.3%
High-Low	-0.9%	-3.1%	-5.3%	-1.7%	-2.3%	-2.6%
t (High-Low)	*-0.23*	*-1.26*	*-2.21*	*-0.62*	*-0.64*	*-1.07*

TABLE 4.10 (Continued). International results

	Small	2	3	4	Large	All
Panel 2. Sorts on market capitalization						
Panel 2A. Debt-to-assets						
Low risk	9.4%	7.2%	8.8%	7.9%	7.7%	8.5%
Mid	10.7%	10.9%	8.9%	8.6%	7.7%	9.0%
High risk	9.5%	6.6%	6.1%	6.6%	5.8%	7.4%
High-Low	0.0%	-0.6%	-2.5%	-1.2%	-1.8%	-1.0%
t (High-Low)	*0.02*	*-0.33*	*-1.46*	*-0.64*	*-1.03*	*-0.69*
Panel 2B. Distance-to-default						
Low risk	9.2%	7.9%	9.4%	9.3%	8.7%	8.8%
Mid	9.1%	7.3%	7.1%	7.8%	7.9%	8.1%
High risk	11.6%	9.5%	6.9%	6.1%	4.5%	7.9%
High-Low	2.2%	1.5%	-2.2%	-2.9%	-3.8%	-0.8%
t (High-Low)	*0.67*	*0.55*	*-0.88*	*-1.27*	*-1.67*	*-0.33*
Panel 2C. Credit spread						
Low risk	13.6%	12.2%	11.9%	8.5%	9.3%	11.1%
Mid	15.6%	13.4%	11.1%	11.5%	7.5%	11.2%
High risk	8.2%	7.9%	9.8%	6.6%	7.4%	9.1%
High-Low	-4.8%	-3.9%	-1.8%	-1.8%	-1.8%	-1.8%
t (High-Low)	*-1.44*	*-1.56*	*-0.87*	*-0.92*	*-0.83*	*-0.89*
Panel 2D. Credit rating						
Low risk	16.5%	13.5%	11.7%	10.6%	9.0%	12.1%
Mid	15.7%	12.6%	12.9%	11.7%	9.6%	12.7%
High risk	11.2%	7.5%	9.8%	8.1%	6.6%	9.2%
High-Low	-4.6%	-5.2%	-1.7%	-2.3%	-2.2%	-2.6%
t (High-Low)	*-1.08*	*-1.79*	*-0.72*	*-1.07*	*-0.75*	*-1.09*

negative relation between the value premium and distress risk. More specifically, only when distance-to-default is used as a measure for distress risk, we observe that high-risk value stocks earn a higher return than low-risk value stocks. The differences between the returns of the other high-minus-low-risk value portfolios range between -0.7 percent when distress risk is measured using the debt-to-assets ratio to -5.7 percent when credit spread is used as a measure for distress risk.

We next analyze the relation between the small-cap premium and distress risk from an international perspective. We observe an international small-cap premium of 1.7 percent per annum, similar in size as the US small-cap premium. However, we do not observe that the higher returns of small-cap stocks are concentrated in the high-risk segment. Results are presented in Panel 2. Actually, we observe that the return of high-risk small-cap stocks is equal to the return of low-risk small-cap stocks when debt-to-assets is used as a measure of distress risk, and we find a return differential of -4.8 percent and -4.6 percent between high- and low-risk small-cap stocks when credit spread and credit rating are respectively used to measure distress risk. In addition, if the small-cap premium is a compensation for distress risk we should simultaneously observe that the lower return of large-cap stocks is concentrated in the low-risk segment. However, in all four cases we observe that high-risk large-cap stocks earn returns down to -3.8 percent lower compared to low-risk large-cap stocks. To conclude, also in an international context, we find no relationship between distress risk and the value and size premiums.

4.9. Profitability and investment effects

In a recent paper Fama and French (2015) document that stock returns are not only related to the market, market capitalization, and valuation, but that returns are also driven by profitability and investment patterns. More specifically, Fama and French report that a firm's operating profitability is positively related to stock returns, and that a firm's change in asset growth is negatively related to returns. In this section we investigate if these factors that are more recently documented by Fama and French in some way are related to distress risk. To this end we perform analyses similar to the triple sorts we conducted earlier. However, we now sort stocks on their operating profitability and their change in assets. For the sake of brevity, these results are not presented in tabular form.

We first consider the results for sorts on profitability. When we consider the return patterns for the triple sorted portfolios, our first observation is that stocks of firms with high profitability generally outperform stocks of firms with lower profitability. At the same time, however, we find no evidence that stocks of firms with high profitability are more risky. Irrespective of which measure we use for risk, it does not appear to be the case that the high profitability portfolios are associated with relatively higher debt-to-assets ratios, smaller distances-to-default, higher spreads, or lower credit ratings. Also, when we consider the returns of the portfolios it does not appear to be the case that the higher returns of the high profitability portfolios are concentrated in the high risk dimension. All in all, these results are inconsistent with the interpretation that the profitability premium is attributable to distress risk.

For the investments effect we find similar results: it does not appear to be the case that stocks of firms with small or negative change in assets have a larger debt-to-equity ratio, lower distance-to-default, higher credit spread, or lower credit rating. Also, it does not appear to be the case that the higher returns are systematically concentrated in the portfolios with the higher risk profiles. These results are also inconsistent with the notion that the investments premium is attributable to distress risk.

4.10. Results for all stocks in U.S. Broad Market Index

All the analyses in our study are based on the 1,500 largest stocks of the Citigroup U.S. BMI. To ensure that our findings are not prone to market micro-structure concerns we have intentionally left out micro-cap stocks from our sample. In this section we examine the sensitivity of our results for our choice of eliminating micro-caps by investigating the relation between the value and size premium and distress risk on all stocks in the Citigroup U.S. BMI. This universe contains on average 2,900 stocks during our sample period.

We start by sorting all stocks into quintile portfolios based on their book-to-market ratio. We observe a large value premium of 7.1 percent per annum, which is larger than the 5.3 percent we observed for the 1,500 largest stocks. To investigate the relation between the value premium and distress risk, we construct size-neutral triple-sorted risk portfolios, as in Table 4.2. We first investigate if high-distress-risk stocks earn higher returns than low-distress-risk stocks. Interestingly, for all four measures of distress risk we find a weaker relation compared to our earlier results on the 1,500 largest stocks. Specifically, only for the debt-to-assets ratio we observe a positive return spread of 0.4 percent between high-risk stocks and low-risk stocks. For the other measures of distress risk as proxied by the distance-to-default, credit spread and credit rating we observe a 3.8, 5.6, and 3.6 percent lower return, respectively, for high-risk compared to low-risk stocks. We next examine the relation between the value premium and distress risk. We observe that by including micro-caps in our universe, the high-minus-low-risk return spread of value stocks becomes considerably more negative. For the debt-to-assets ratio this spread turns negative from 0.2 percent to -4.4 percent. For the distance-to-default, credit spread and credit rating this difference decreases from -1.8, -3.7 and -1.9 percent to -8.6, -12.4 and -5.7 percent, respectively.

When we include micro-caps in our universe we observe a negative size premium of 2.15 percent. Compared to our earlier results in Table 4.6 for the 1,500 largest stocks, we observe that the relation between the small-cap premium and distress risk becomes even more negative. The return between high- and low-risk small-cap stocks ranges from -5.7 percent for the debt-to-assets ratio to -20.1 percent for the credit spread. We therefore conclude that also when we include micro-caps in our universe that distress risk is unlikely to explain the value and small-cap premiums.

4.11. Concluding comments

Following the work of Fama and French (1992, 1993), a large stream of literature has been developed on the small-cap and value anomalies and numerous attempts have been made to better understand the economic origin of these anomalies. In particular, several papers attribute the small-cap and value anomalies to a common risk factor and contend that the premiums are compensation for investors bearing distress risk. Notably, there are also some papers that dispute this assertion and document that it is unlikely that the small-cap and value premiums can be attributed to distress risk. One potential reason that the results in the literature seem to conflict is that different measures and methodologies are used in the studies. This study contributes to the extant literature in the following ways.

First of all, we contribute to the existing literature by drawing a unified conclusion regarding the pricing of distress risk in the cross-section of stock returns. We show that no positive relation can be found between risk and returns.

Second, we show that both the small-cap and the value premiums are not concentrated in distressed stocks. Irrespective of whether we measure stocks' probabilities on financial distress using accounting models, structural models, credit spreads or credit ratings, we find that the premiums cannot be absorbed by distress risk. The results are also robust to the method that is used to investigate the relation between the two variables. Irrespective of whether we use rank portfolios, business cycle analyses à la Lakonishok, Shleifer and Vishny (1994), or cross-sectional Fama-MacBeth (1973) regressions, we find no positive relation between the small-cap and value premiums and distress risk. Our results also help to understand the results of several studies that report that the small-cap premium is no longer present after the early 1980s.

Finally, our results indicate that the empirical explanatory power of the Fama-French (1993) SMB and HML factors cannot be attributed to these factors being exposed to distress risk. We construct new factors that disentangle the size and value effects from distress risk.

Overall, our results are difficult to reconcile with a risk-based interpretation of the value anomaly and call for further research on the development and testing of theories that potentially provide an explanation for the size and value effects.

5. The low-risk anomaly and mutual fund tournaments[54]

I examine the relationship between tournament behavior of mutual fund managers and the low-risk anomaly. Based on a general equilibrium model, I show that tournament behavior causes the returns of low-risk (high-risk) assets to be larger (smaller) than expected from the Capital Asset Pricing Model. Using data on mutual funds and prices of individual assets from twelve different asset categories, I find a positive and significant relation between tournament behavior and the low-risk premium. The results indicate that not only is the low-risk effect more prominent in a period following stronger tournament behavior, but the anomaly is also larger in asset categories where more tournament behavior is observed. As a consequence, these insights are important for investors aiming to capture the low-risk premium.

5.1. Introduction

The prevalence of delegated asset management has increased substantially over the past 5 decades. Whereas 50 years ago the vast majority of US corporate equity was held by individual investors, intermediaries currently hold over half of assets. As a consequence, the incentives of such intermediaries can potentially impact the way assets in the economy are priced. In this study I explore the influence on asset prices of one robustly documented phenomenon in the asset management industry: tournament behavior between fund managers. I show that tournament behavior can go a long way towards explaining an asset-pricing anomaly that is receiving increasing attention: the low-risk anomaly.

Intuitively, assets with high systematic risk provide higher average returns than low-risk assets, proportional to their risk levels. Theoretically, this intuition is reflected by the Capital Asset Pricing Model (CAPM), which describes the relation between risk, as measured by beta, and expected return. However, empirically there is ample evidence that this relation is flatter than expected [e.g. Black et al. (1972)][55], also known as the low-risk anomaly.

[54] This chapter is based on De Groot, W., 2017, The low-risk anomaly and mutual fund tournaments, *working paper*.

[55] Black et al. (1972) and Haugen and Heins (1975) have already documented the low-risk anomaly within US equities. Also Fama and French (1992) found that the relationship between risk and return was flat. Blitz and Van Vliet (2007) have extended this to Europe and Japan and show that stocks with a low volatility generate higher risk-adjusted returns than stocks with a high volatility. Recently, Frazzini and Pedersen (2014) find that also for Treasury bonds, corporate bonds and futures, low-beta securities earn higher alphas than high-beta securities.

Not all CAPM assumptions might hold for fund managers who invest for others (clients and/or employers). According to the CAPM, an investor requires a higher return on more risky assets as measured by beta. An important assumption of the model is that investors are averse to risk and that they are only interested in maximizing the expected utility of their end-of-period wealth. However, one well-documented form of fund manager's behavior not captured by the CAPM is tournament behavior, which implies that it is *not* (only) the objective of investors to maximize the client's wealth.

Tournament behavior refers to the behavior where fund managers aim to win the 'tournament' (i.e. achieve the highest returns compared to peers). This could be because the size of their remuneration might depend on their performance relative to other participants, but also because of other reasons, such as competitive behavior of fund managers. A fund manager belonging to the mid-term loser funds where funds are ranked on performance, can increase chances of ending higher on the ranking at the end of the term by taking more risk. Brown et al. (1996) were one of the first who demonstrated the existence of tournament behavior for US mutual funds during 1980 to 1991 by showing that mid-year loser funds more often increase their risk in the second half of the year than mid-year winner funds. Many follow-up studies confirmed the existence of tournament behavior.

Hence, tournament behavior implies that fund managers of loser funds increase their portfolio risk. If leverage is unrestricted and cheap, taking more leverage is a way to increase risk. However, if leverage is restricted and/or costly, which is the case for most mutual fund managers, high-risk securities become more attractive and fund managers are prepared to pay a premium that decreases the return on these high-risk securities. An intuitive implication of tournament behavior among mutual fund managers is therefore the existence of the low-risk anomaly. The objective of this study is to theoretically investigate the impact of this behavior on the prices of high- and low-risk assets and empirically establish whether there is a relation between tournament behavior and the low-risk anomaly.

An advantage of investigating tournament behavior as a measure to explain the low-risk anomaly is that it is asset class specific in the sense that whether tournament behavior is present and how strong it is can differ among asset classes and time. The same might hold for the low-risk premium. It could well be the case that the periods that low-risk securities outperform high-risk securities differs across asset classes, in other words, that the low-risk premium between asset classes is not highly correlated. If this holds, then it is logical to use a measure which is asset-class specific when explaining the low-risk anomaly. However, several studies have used global factors that are not asset-class specific, such as TED-spread and inflation which are used by Frazzini and Pedersen (2014) and Cohen et al.

(2005), respectively. In the following section I give an overview of the existing literature in this field.

I develop a simple general equilibrium model to investigate the impact of tournament behavior across mutual fund managers on prices of high- and low-risk assets. The base model is a one-period equilibrium model with two agents who maximize their growth in wealth and two dividend-paying assets: a high- and low-risk asset. I next expand this base model by including tournament behavior. That means that the agents not only maximize their wealth growth, but also maximize the return of their own portfolio compared to that of their peers. The model predicts that tournament behavior causes the returns of low-risk (high-risk) assets to be larger (smaller) than expected according to the CAPM. Based on this model, the following testable hypotheses are defined:

1) The low-risk effect in a particular asset category is stronger in a period following stronger tournament behavior.
2) The low-risk effect is stronger in asset categories where tournament behavior is stronger.

I empirically analyze these predictions within and across asset categories.

To measure tournament behavior, this study makes use of the Morningstar mutual fund database with monthly data from January 1990 to December 2013. The study covers 12 different asset categories, consisting of bond classes, regional equity classes and style sub-classes within US equities. To measure tournament behavior, I use a test statistic in line with Brown et al. (1996) as commonly used in academic literature. I investigate whether mid-year losers take substantially more risk than mid-year winners in the second half of the year. In addition, for each of the asset categories I construct leveraged low-minus-high risk portfolios based on the past year volatility of individual securities.[56]

In the first analysis I find that tournament behavior is generally present, in line with Brown et al. (1996). However, this behavior is time-varying and not present every year within each asset category. It is therefore important to take the time dimension into account when analyzing the relationship between tournament behavior and the low-risk anomaly.

Next, I show that the low-risk anomaly is present in almost all asset categories, consistent with Frazzini and Pedersen (2014). There is a low correlation among the low-risk return series of different asset categories. Due to this finding, it is unlikely that a global risk factor, which is non-asset class specific such as TED-spread and inflation, can fully explain the low-risk anomaly, as used by Frazzini and Pedersen (2014) and Cohen et al. (2005), respectively.

[56] For government bonds I construct low-minus-high risk portfolios based on the maturity of bonds.

To investigate whether, for a particular asset category, the low-risk effect is stronger in a period following stronger tournament behavior, I apply pooled OLS regressions. We observe a positive and significant relation between tournament behavior and the low-risk premium. In addition, we observe that when the sample is split into two sub-periods, the relation is positive and significant in both sample periods. It is thus evident that there is a positive relation between tournament behavior and the low-risk premium over time.

Next, I examine whether the low-risk effect is stronger in asset categories where tournament behavior is stronger. Therefore, for each year in the sample, I sort the asset categories in three terciles based on tournament behavior that year and compute the low-risk returns of the three portfolios in the following year. I observe that the tercile portfolio with the highest tournament behavior performs significantly better than the portfolio with the lowest tournament behavior, on average around 5% per annum. The conclusions do not change or even become somewhat stronger when corrected for loadings on general market returns or structural positions.

To conclude the main empirical analyses, I investigate the impact of tournament behavior on the low-risk premium across asset categories with Fama and MacBeth (1973) regressions. The advantage of this method is that other factors can easily be controlled, such as activeness of the market, market volatility and the risk-adjusted return of the markets. Consistent with the portfolio findings, a positive and significant relation between tournament behavior and the low-risk premium is apparent in most cases.

Finally, I provide several possibilities to extend the theoretical pricing model. One suggestion is that the amount of utility agents get from tournament behavior can be made dependent on the type of market (bull or bear), in line with the findings of Kempf et al. (2009). They show that tournament behavior exists when the first half-year is a bull market and not when it is a bear market. A 2x2 contingency table shows that most observations in the entire sample fall in the 'high tournament behavior/high low-risk premium' and 'low tournament behavior/low low-risk premium' segments. Interestingly, during bull markets most observations are in the 'high tournament behavior/high low-risk premium' segment and during bear markets in the 'low tournament behavior/low low-risk premium' segment. These findings are in line with the hypothesis that mutual fund manager's incentives to perform well are strongest during bull markets. Some studies suggest that besides chasing returns cross-sectionally, mutual fund investors also chase returns through time [Warther (1995)], meaning that large cash inflows occur in a particular asset class just after the market has made an upward rally. Fund managers are therefore incentivized to outperform especially during bull markets, strengthening the higher demand for high-beta stocks and reducing the expected returns of these stocks.

I conclude the empirical analyses by showing that tournaments have most impact on the prices of low- and high-risk asset in the year following the tournaments. When I increase the length of the period to compute the low-risk premium (i.e. the investment horizon), the results become weaker and insignificant. This could be caused by new tournaments that have started where the 'newest' high-risk stocks are being selected and for which the demand is higher than the 'older' high-risk stocks.

To summarize, I develop a theoretical model that describes that tournament behavior causes the expected return of low-risk assets to be higher than expected according to the CAPM. Irrespective of the method I use (pooled OLS-regressions, sorting portfolios, Fama and MacBeth (1973) regressions and contingency tables) there is a positive relation between tournament behavior and the low-risk premium.

To my knowledge, this is the first study to examine the relation between tournament behavior and the low-risk anomaly, both theoretically and empirically across a broad range of asset categories. This study contributes to the literature in several ways. First, the finding of a positive relationship between tournament behavior and the low-risk premium helps to explain the low-risk anomaly across a wide range of asset classes. I acknowledge that other explanations could also play a role. For example, leverage and shorting restrictions could strengthen the positive relation between tournament behavior and the low-risk premium.

The insights of this study could also be valuable for investors in low-risk strategies, as the research potentially gives insight in which markets we can best exploit this anomaly and can therefore guide asset managers as to where to set-up low-risk products. In markets where tournament behavior is absent, the low-risk premiums are expected to be much smaller or not even present. Moreover, the research could give insight in how the anomaly can best be exploited. For example, as tournament behavior seems to be a dominant factor it is logical to capture the premium within universes of competitive funds instead of across universes (e.g. emerging markets and develop markets equities separately instead of an overall comparison). Also, the importance assigned to the low-risk factor when selecting stocks could potentially be adjusted when one predicts whether tournament behavior will be an important factor (e.g. in case of large cash inflows to the asset class).

The structure of the remainder of this chapter is as follows. The next section gives an overview of the relevant literature on the low-risk anomaly and tournament behavior. Section 5.3 provides the theoretical model. Section 5.4 describes the construction of the data set and Section 5.5 presents the empirical results for analyses that examine if there is a relationship between tournament behavior and the low-risk premium. Section 5.6 discusses several possibilities to extend the theoretical model and Section 5.7 concludes.

5.2. Literature

5.2.1. The low-risk anomaly

The literature on explaining the source for the low-risk premium is rather scarce and ambiguous.[57] Only several studies attempt to identify the source of the low-risk premium. First, Black (1972) uses a theoretical model and argues that borrowing restrictions are the reason for the relatively high performance of low-beta stocks. The idea is that some market participants cannot use leverage to increase portfolio risk and therefore overweight high-beta securities, leading to lower returns on these assets. Frazzini and Pedersen (2014) provide empirical support for this hypothesis by using the TED-spread as a proxy for funding constraints. However, this factor only seems to relate (weakly) to the low-risk premium in equity markets. In most other asset classes (government bonds, credits, FX and commodities) the relation between TED-spread and the low-risk premium is opposite to what their hypothesis predicts. In relation to leverage constraints, the literature also discusses short-selling constraints, as a cause of the low-risk anomaly. For example, Hong and Sraer (2016) show that short-sales constraints in combination with investors' disagreement about the future prospects of the stock market result in high beta stocks being overpriced. A second explanation is from Cohen et al. (2005) who argue that the risk-return relationship in the US stock market is flatter during high-inflation environments and relate this to the money-illusion hypothesis. Third, Karceski (2002) developed an agency model where return-chasing behavior by mutual fund investors causes beta not to be priced to the degree predicted by the standard CAPM. Other explanations are from Baker et al. (2011) and Bali et al. (2011) who suggest that behavioral biases, such as a preference for lotteries, are the cause of the low-risk anomaly.

To conclude, the few existing empirical studies that attempt to explain the low-risk anomaly use global factors that are not asset-class specific, such as TED-spread and inflation. However, these measures will only be able to explain the low-risk effect across different asset classes in case of a relatively high correlation between the low-risk premiums of different asset classes. Moreover, although the theoretical model developed by Karceski

[57] Blitz, Falkenstein and Van Vliet (2014) provide a literature overview of possible explanations for the low-risk effect.

(2002) on mutual fund investors' behavior is compelling and can be asset-class specific, it is not empirically tested.

5.2.2. Tournament behavior

Although Brown et al. (1996) were one of the first who demonstrated the existence of tournament behavior for US mutual funds, many follow-up studies confirmed the existence of tournament behavior. For example Elton, Gruber, and Blake (2003), Hu, Kale, Pagani, and Subramaniam (2011) and Swarz (2012). Kempf et al. (2009) confirm that tournament behavior exists based on mutual fund holdings data, but argue it is dependent on the market return in the first half-year.

One of the explanations given for tournament behavior is that mutual fund investors tend to chase returns over time and across funds. The main objective of a fund manager is to maximize the profits for the organization, because then she will receive the highest rewards. This implies that it is *not* (only) her objective to maximize the client's wealth. In order to achieve high fund profits, she needs to increase the assets under management or, in other words, to maximize cash inflows.

As mutual fund investors buy funds with the highest recent past returns, a 'winner-takes-it-all' structure holds for many asset classes. This means that most of the cash inflows go to a few winners [see e.g. Sirri and Tufano (1998) who show that this relation holds for US equity mutual funds and Brown et al. (2001) for hedge funds and CTAs]. As, in addition, cash is not easily withdrawn from loser funds with the lowest recent past returns, this is also called an asymmetric flow-performance relation. To belong to the winners, a loser fund could therefore take higher risk to win the tournament.

5.3. Theoretical model

In this section I present a general equilibrium model where tournament behavior causes high-risk assets to have a lower return and low-risk assets to have a higher return than expected according to the CAPM.

5.3.1. Model without tournament behavior

5.3.1.1. Technology

Let us assume the model has two dates (t=0 and t=1). The economy I study consists of two agents A and B and two types of assets, a high-risk asset H and a low-risk asset L. The payoff (or dividend) of these assets (at t=1) are normally distributed[58],

(5.1) $$D_{H1} = N(\mu, \sigma_H^2)$$
$$D_{L1} = N(\mu, \sigma_L^2)$$

where D_{H1} is the payoff on the high-risk asset at the end of the period and D_{L1} the payoff on the low-risk asset and $\sigma_H > \sigma_L$. The advantage of assuming normally distributed returns is that later on, when solving the model, the solution has a closed form. The correlation between the payoffs is denoted by ρ. Both assets are in unit supply, so that expected returns in equilibrium are determined by aggregate demands.

5.3.1.2. Preferences

I denote the demand of agents A and B for assets H and L as $q_{AH}, q_{AL}, q_{BH}, q_{BL}$, respectively. The agents invest their wealth in the two assets with price P_{H0} defined as the price of the high-risk asset at the beginning of the period (t=0) and P_{L0} as the price of the low-risk asset. The wealth of the two agents at the beginning of the period is therefore defined by:

(5.2) $$W_{A0} = q_{AH}P_{H0} + q_{AL}P_{L0}$$
$$W_{B0} = q_{BH}P_{H0} + q_{BL}P_{L0}$$

And at the end of the period (t=1) by:

(5.3) $$W_{A1} = q_{AH}D_{H1} + q_{AL}D_{L1}$$
$$W_{B1} = q_{BH}D_{H1} + q_{BL}D_{L1}$$

Let us for now assume that tournament behavior does not exist. For simplicity reasons I assume that the two agents have the same utility function, defined as:

[58] We assume equal expectations for the two assets. Assuming unequal expected pay-offs does not change the conclusions.

(5.4)
$$U_A = -\exp(-\theta_A(W_{A1} - W_{A0}))$$
$$U_B = -\exp(-\theta_B(W_{B1} - W_{B0})),$$

where $\theta_i > 0$ for i={A,B} is the agent's risk aversion coefficient. Assuming exponential utility functions is for ease of computation.

5.3.1.3. Solving the model

At t=0, the agents choose the weights of the high- and low-risk asset to maximize their expected utility. Let us continue from the perspective of agent A:

(5.5)
$$\max_{q_{AH},q_{AL}} E[-\exp(-\theta_A(W_{A1} - W_{A0}))]$$
$$= \max_{q_{AH},q_{AL}} E[-\exp(-\theta_A\{q_{AH}(D_{H1} - P_{H0}) + q_{AL}(D_{L1} - P_{L0})\})]$$

Because of the normally distributed asset returns, the expectation operator in Equation 5.5 can be rewritten as:

(5.6)
$$\max_{q_{AH},q_{AL}} \begin{matrix} -\exp(-\theta_A\{q_{AH} + q_{AL}\}\mu + \theta_A q_{AH} P_{H0} + \theta_A q_{AL} P_{L0} + \\ \frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2 + q_{AL}^2\sigma_L^2 + 2\rho q_{AH} q_{AL}\sigma_H\sigma_L\}) \end{matrix}$$
$$= \max_{q_{AH},q_{AL}} \begin{matrix} (\theta_A\{q_{AH} + q_{AL}\}\mu - \theta_A q_{AH} P_{H0} - \theta_A q_{AL} P_{L0} - \\ \frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2 + q_{AL}^2\sigma_L^2 + 2\rho q_{AH} q_{AL}\sigma_H\sigma_L\}) \end{matrix}$$

This optimization problem can be solved by taking the first derivative with respect to q_{AH}:

(5.7)
$$\theta_A\mu - \theta_A P_{H0} - \theta_A^2 q_{AH}\sigma_H^2 - \theta_A^2\rho q_{AL}\sigma_H\sigma_L = 0$$

This leads to the following optimal solution for q_{AH}:

(5.8)
$$q_{AH} = \frac{\mu - P_{H0} - \theta_A\rho q_{AL}\sigma_H\sigma_L}{\theta_A\sigma_H^2}$$

From Equation 5.8 it follows that agent A will allocate more to the high-risk asset in case the price at t=0 is lower. Also, the demand for the asset is decreasing in the standard deviation of the pay-off.

Solving the problem for q_{AL} as well and also taking the perspective of agent B, leads to the following set of equations combined with the unit supply constraints:

(5.9)
$$q_{AH} = \frac{\mu - P_{H0} - \theta_A \rho q_{AL} \sigma_H \sigma_L}{\theta_A \sigma_H^2}$$
$$q_{AL} = \frac{\mu - P_{L0} - \theta_A \rho q_{AH} \sigma_H \sigma_L}{\theta_A \sigma_L^2}$$
$$q_{BH} = \frac{\mu - P_{H0} - \theta_B \rho q_{BL} \sigma_H \sigma_L}{\theta_B \sigma_H^2}$$
$$q_{BL} = \frac{\mu - P_{L0} - \theta_B \rho q_{BH} \sigma_H \sigma_L}{\theta_B \sigma_L^2}$$
$$q_{AH} + q_{BH} = 1$$
$$q_{AL} + q_{BL} = 1$$

5.3.1.4. Model analysis

Let us have a look at the intuition behind the model with the help of an example. In the example, I assume that agent A and agent B both have a risk-aversion parameter of $\theta_A = \theta_B = 0.01$. Further assuming that both assets have an expected payoff $\mu = 100$ and that the correlation between the assets $\rho = 0.5$. The volatility of the high-risk asset $\sigma_H = 30$ and the volatility of the low-risk asset $\sigma_L = 20$. The solution of the six equations with six unknowns is that both agents hold equal amounts of the high- and low-risk asset: $q_{AH} = q_{BH} = q_{AL} = q_{BL} = 0.5$. The price of the high-risk asset P_{H0}= 94 and the price of the low-risk asset P_{L0}= 96.5. As the risk is higher for the high-risk asset, the expected risk premium is higher and the price is lower. The return of the high-risk asset is defined as:

(5.10)
$$R_{H1} = \frac{D_{H1}}{P_{H0}} - 1$$

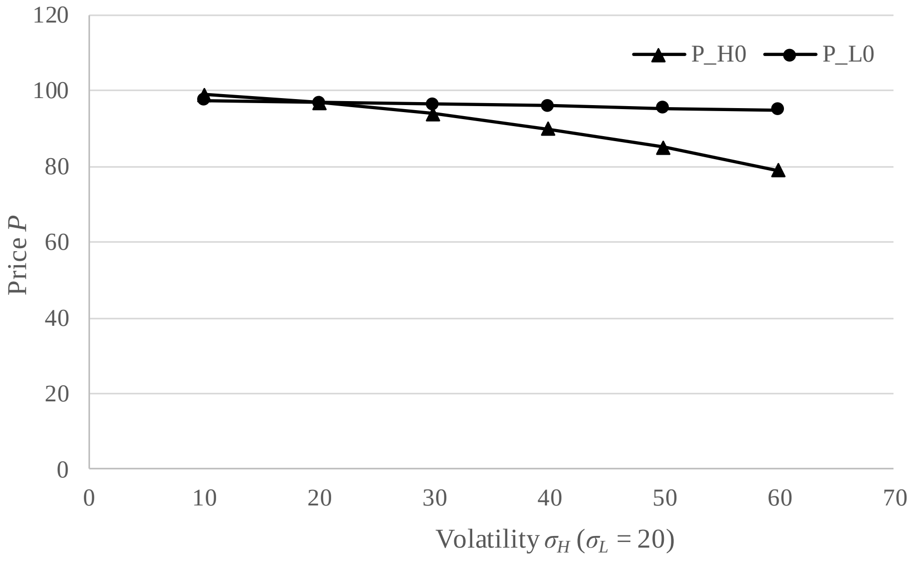
The expected return of the high-risk asset is therefore:

(5.11)
$$E[R_{H1}] = \frac{E[D_{H1}]}{P_{L0}} - 1 = \frac{\mu}{P_{H0}} - 1$$

When we fill in the numbers in the example, an expected return of 6.4% for the high-risk asset and 3.6% for the low-risk asset is found. The higher the risk of the high- versus the low-risk asset, the higher the expected risk premium and the lower the price of the high-risk asset versus the low-risk asset as visible from Figure 5.1.

FIGURE 5.1. Relation between price and volatility of the high- and low-risk asset in the model without tournament behavior

The figure shows the price of the high- and low-risk asset (P_{H0} and P_{L0}, respectively) for different volatility levels of the high-risk asset (σ_H). The volatility of the low-risk asset σ_L is kept at 20. Agent A and agent B have a risk-aversion parameter of $\theta_A = \theta_B = 0.01$. Both assets have an expected payoff $\mu = 100$ and the correlation between the assets is $\rho = 0.5$.



Let us now assume that agent B is more risk-averse than agent A. We then expect agent B to hold less of the assets compared to agent A. Figure 5.2 shows that this is indeed the case in our example.

5.3.2. Model with tournament behavior

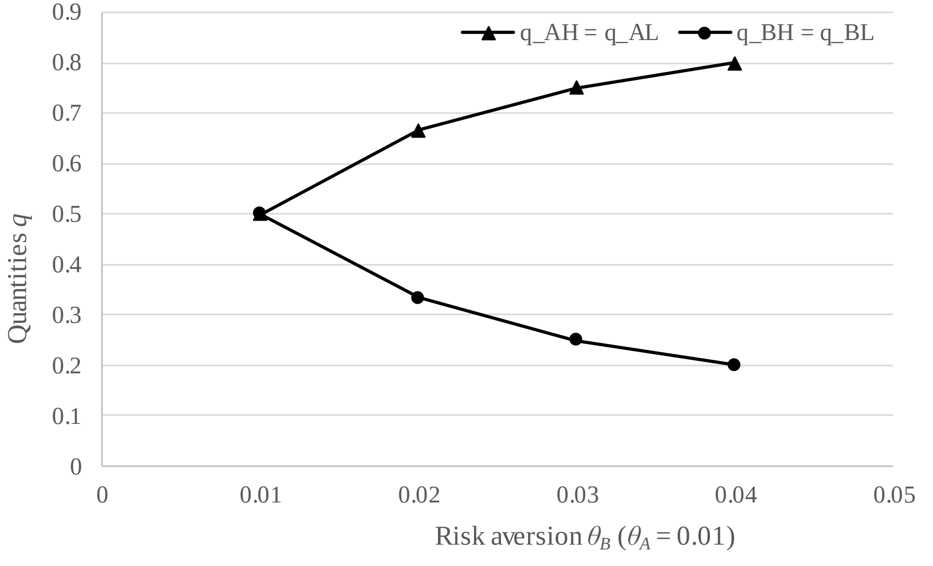
In this sub-section I extend the model by including tournament behavior. The assets follow the same distribution as in the previous sub-section. However, the agent's preferences are different.

5.3.2.1. Preferences

The agents now not only maximize their change in asset wealth, but also maximize the return of their own portfolio compared to that of their peers. The return of agent A is given by:

(5.12) $R_A = w_{AH}R_{H1} + w_{AL}R_{L1},$

FIGURE 5.2. Relation between the quantities the agents own of the assets and the risk-aversion of agent B compared to agent A in the model without tournament behavior
The figure shows the quantities of the high- and low-risk asset (q_H and q_L, respectively) for different risk aversion parameter values of agent B (θ_B). The risk aversion parameter of agent A is kept at 0.01. The volatility of the high-risk asset $\sigma_H = 30$ and the volatility of the low-risk asset $\sigma_L = 20$. Both assets have an expected payoff $\mu = 100$ and the correlation between the assets is $\rho = 0.5$.



where the portfolio weight of asset H for agent A is defined by:

$$(5.13) \qquad w_{AH} = \frac{q_{AH}P_{H0}}{q_{AH}P_{H0}+q_{AL}P_{L0}}$$

Similar definitions apply for the return of agent B and the other portfolio weights.

I assume a linear relation between tournament behavior and utility, but obviously other functional forms can also be applied. The utility function for agent A and agent B is now respectively defined by:

$$(5.14) \qquad \max_{q_{AH},q_{AL}} E\left[-\exp\left(-\theta_A(W_{A1}-W_{A0})\right)+\eta_A(R_A-R_B)\right]$$

$$\max_{q_{BH},q_{BL}} E\left[-\exp\left(-\theta_B(W_{B1}-W_{B0})\right)+\eta_B(R_B-R_A)\right],$$

where η is the parameter that indicates the sensitivity towards tournament behavior. For simplicity, tournament behavior for agent B is normalized to zero, so $\eta_B = 0$. This means that the first order conditions for agent B remain the same as in the case without tournament behavior.[59]

5.3.2.2. Solving the model

The maximization problem for agent A can be rewritten to:

$$(5.15) \quad \max_{q_{AH}, q_{AL}} E[-\exp(-\theta_A\{q_{AH}(D_{H1} - P_{H0}) + q_{AL}(D_{L1} - P_{L0})\}) + \eta_A(w_{AH}R_{H1} + w_{AL}R_{L1} - w_{BH}R_{H1} - w_{BL}R_{L1})],$$

Solving for q_{AH} leads to the following equation (see Appendix 5.A):

$$(5.16) \quad -\exp(-\theta_A\{q_{AH} + q_{AL}\}\mu + \theta_A q_{AH} P_{H0} + \theta_A q_{AL} P_{L0} + \frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2 + q_{AL}^2\sigma_L^2 + 2\rho q_{AH} q_{AL}\sigma_H\sigma_L\}) * (-\theta_A\mu + \theta_A P_{H0} + \theta_A^2 q_{AH}\sigma_H^2 + \theta_A^2\rho q_{AL}\sigma_H\sigma_L) + \frac{\eta_A(\mu - P_{H0})(q_{AH}P_{H0} + q_{AL}P_{L0}) - P_{H0}\eta_A(\mu - P_{H0})q_{AH} - P_{H0}\eta_A(\mu - P_{L0})q_{AL}}{(q_{AH}P_{H0} + q_{AL}P_{L0})^2} = 0$$

Solving the problem for q_{AL} as well leads to the following equation:

$$(5.17) \quad -\exp(-\theta_A\{q_{AH} + q_{AL}\}\mu + \theta_A q_{AH} P_{H0} + \theta_A q_{AL} P_{L0} + \frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2 + q_{AL}^2\sigma_L^2 + 2\rho q_{AH} q_{AL}\sigma_H\sigma_L\}) * (-\theta_A\mu + \theta_A P_{L0} + \theta_A^2 q_{AL}\sigma_L^2 + \theta_A^2\rho q_{AH}\sigma_H\sigma_L) + \frac{\eta_A(\mu - P_{L0})(q_{AH}P_{H0} + q_{AL}P_{L0}) - P_{L0}\eta_A(\mu - P_{L0})q_{AL} - P_{L0}\eta_A(\mu - P_{H0})q_{AH}}{(q_{AH}P_{H0} + q_{AL}P_{L0})^2} = 0$$

The first order conditions of agent B and the unit supply constraints remain the same:

$$(5.18) \quad q_{BH} = \frac{\mu - P_{H0} - \theta_B\rho q_{BL}\sigma_H\sigma_L}{\theta_B\sigma_H^2}$$

$$q_{BL} = \frac{\mu - P_{L0} - \theta_B\rho q_{BH}\sigma_H\sigma_L}{\theta_B\sigma_L^2}$$

[59] Note that the model now only assumes tournament behavior and makes no assumptions on why tournament behavior exists. This could be due to a variety of reasons, or simply because the agents are competitive by nature.

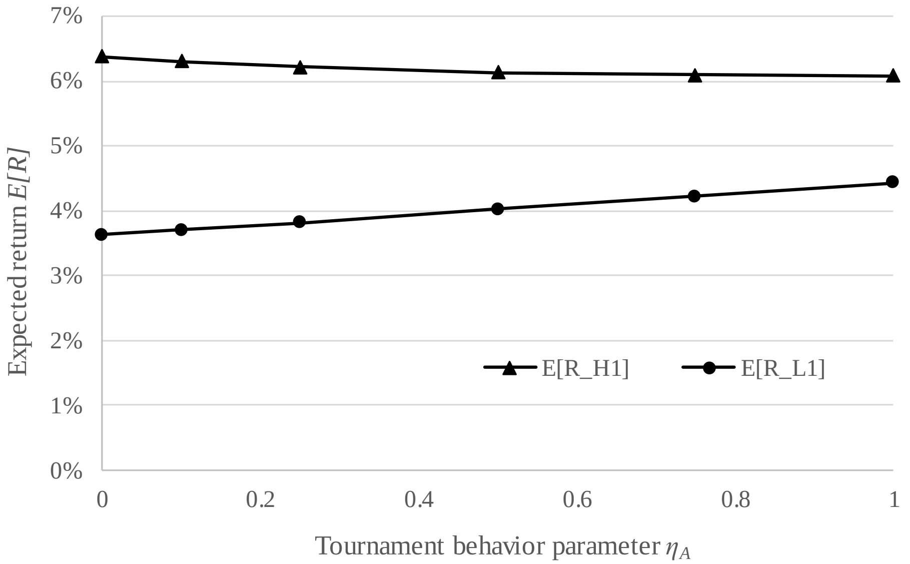
$$q_{AH} + q_{BH} = 1$$
$$q_{AL} + q_{BL} = 1$$

5.3.2.3. Model analysis

Let us now investigate how the inclusion of tournament behavior influences the risk/return relation of the high- and low-risk assets in the example of Sub-section 5.3.1.4.

FIGURE 5.3. Relation between expected return of the high- and low-risk asset and tournament behavior in the model with tournament behavior

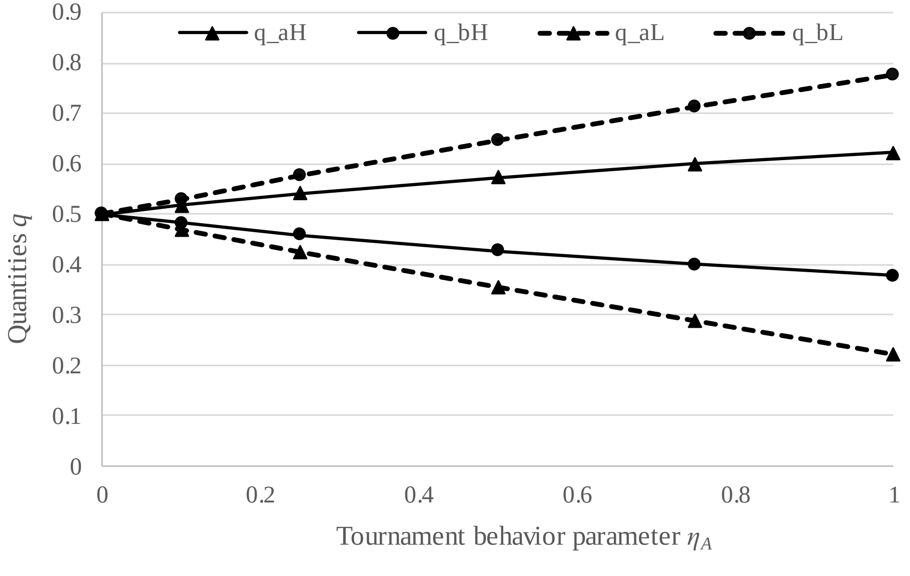
The figure shows the expected returns of the high- and low-risk asset ($E[R_{H1}]$ and $E[R_{HL}]$) for different tournament behavior parameter values of agent A (η_A). Agent B does not get utility from tournament behavior, so $\eta_B = 0$. Agent A and agent B have a risk-aversion parameter of $\theta_A = \theta_B = 0.01$. The volatility of the high-risk asset $\sigma_H = 30$ and the volatility of the low-risk asset $\sigma_L = 20$. Both assets have an expected payoff $\mu = 100$ and the correlation between the assets is $\rho = 0.5$.



From Figure 5.3 we observe the impact when agent A also gets utility from tournament behavior. In case agent A does not have tournament behavior ($\eta_A = 0$), we logically get similar expected return as in Sub-section 5.3.1.4: an expected return of 6.4% for the high-risk asset and 3.6% for the low-risk asset. The more utility agent A gets from tournament behavior, the higher the demand for the high-risk asset. As a consequence, we expect the high-risk asset to have a higher price and a lower expected risk premium. Similarly, tournament behavior lowers the demand of agent A for the low-risk asset. Agent B will need to hold more of the low-risk asset, but is only willing to do that if the price is low enough and therefore the expected risk premium high enough. This is in line with what we observe in Figure 5.3. In addition, the expected return of the low-risk asset remains lower than that of the high-risk asset; so the security market line becomes flatter, but not inverse.

Figure 5.4 shows the quantities agents A and B hold of the high- and low-risk asset when tournament behavior is included in the model. We observe that agent A indeed holds more of the high-risk asset at the expense of the low-risk asset, the more important tournament behavior becomes. Due to the unit supply constraints and the lower price of the low-risk asset, agent B holds more of the low-risk asset.

FIGURE 5.4. Relation between quantity and tournament behavior of the high- and low-risk asset in the model with tournament behavior
The figure shows the quantities of the high- and low-risk asset (q_H and q_L, respectively) hold by agent A and agent B for different tournament behavior parameter values of agent A (η_A). Agent B does not get utility from tournament behavior, so $\eta_B = 0$. Agent A and agent B have a risk-aversion parameter of $\theta_A = \theta_B = 0.01$. The volatility of the high-risk asset $\sigma_H = 30$ and the volatility of the low-risk asset $\sigma_L = 20$. Both assets have an expected payoff $\mu = 100$ and the correlation between the assets is $\rho = 0.5$.



Next, we can investigate the impact of tournament behavior on expected alpha. As the CAPM-model does not hold anymore, we expect alpha to be non-zero. I therefore compute the CAPM-beta and the expected alpha of the high- and low-risk asset. The market portfolio return is defined as:

(5.19) $R_{M1} = w_L R_{L1} + w_H R_{H1}$, where

$$w_L = \frac{P_{L0}}{P_{H0}+P_{L0}}$$

$$w_H = \frac{P_{H0}}{P_{H0}+P_{L0}}$$

The CAPM-beta and expected alpha are the usual[60]:

(5.20) $\beta_{H,M} = \frac{cov(R_{H1}, R_{M1})}{var(R_{M1})}$

(5.21) $\alpha_{H1} = E[R_{H1}] - \beta_{H,M}E[R_{M1}]$

FIGURE 5.5. Relation between expected alpha and tournament behavior of the high- and low-risk asset in the model with tournament behavior

The figure shows the expected alpha of the high- and low-risk asset (α_{H1} and α_{L1}) for different tournament behavior parameter values of agent A (η_A). Agent B does not get utility from tournament behavior, so $\eta_B = 0$. Agent A and agent B have a risk-aversion parameter of $\theta_A = \theta_B = 0.01$. The volatility of the high-risk asset $\sigma_H = 30$ and the volatility of the low-risk asset $\sigma_L = 20$. Both assets have an expected payoff $\mu = 100$ and the correlation between the assets is $\rho = 0.5$.

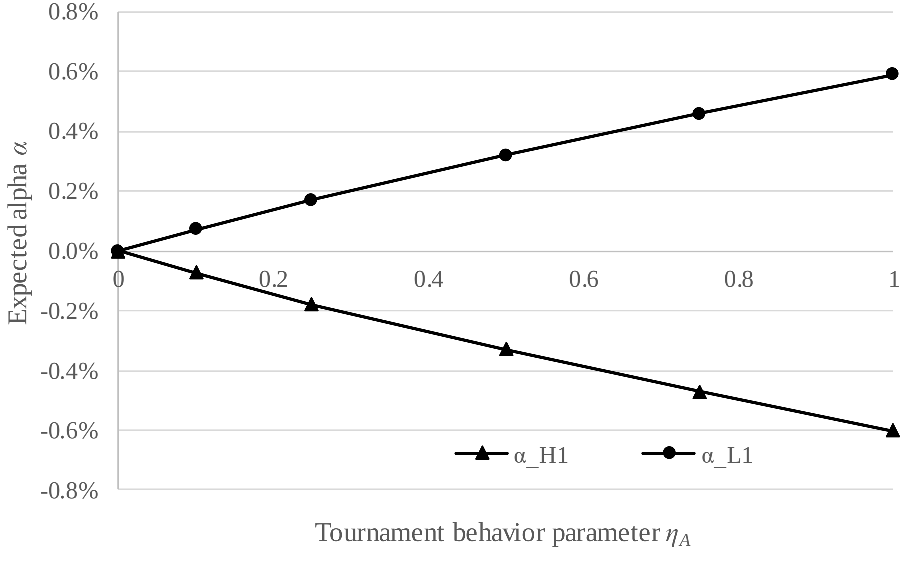


Figure 5.5 shows the expected alpha of the two assets as a function of tournament behavior. When there is no tournament behavior we observe that the expected alpha of the assets is zero; in other words, CAPM holds. When tournament behavior becomes more important, we observe that the low-risk asset gets a positive expected alpha, while the high-risk asset gets a negative expected alpha. In summary, according to the model, tournament behavior causes higher (lower) returns on low-risk (high-risk) assets then when tournament

[60] See Appendix 5.B for details.

behavior is absent. Moreover, the stronger the tournament behavior, the higher (lower) the return on low-risk (high-risk) assets are or, in other words, the stronger the anomaly.

5.3.2.4. Hypotheses

I continue by defining hypotheses which can be tested empirically. Even though the model illustrates the main mechanism using a parsimonious setup with two assets and agents, the general intuition will likely extend to multiple assets and agents. The reason is that when there are more than two assets with different volatilities, the preference for high-risk assets for an agent with tournament behavior remains. The higher demand for high-risk assets, will reduce the expected alpha of these assets in comparison to low-risk assets. Furthermore, in case multiple agents exhibit tournament behavior, the demand for high-risk assets will increase, which causes the expected alpha of these assets to decrease. This holds, even if the managers do not equally care about tournaments, yet some exhibit stronger tournament behavior than others.

As tournament behavior causes managers of similar mutual funds to compete with each other, these competing managers choose assets within one particular asset category. For example, managers of US large-cap mutual funds are all searching for the best stocks out of the same universe of US large-cap stocks with the aim to win the tournament. If tournament behavior is a cause for the low-risk anomaly, I expect the low-risk premium to be present within asset classes, but not across asset classes. The majority of the studies related to the low-risk anomaly, focus on the premium within asset classes and there seems to be little evidence for the low-risk anomaly across asset classes. Moreover, the presence of a positive equity risk premium seems to imply that there is no low-risk effect across asset classes.

Based on Figure 5.5, I expect that when there is no tournament behavior within an asset category, there is also no low-risk premium and the stronger the tournament behavior, the stronger the anomaly. As there are many asset categories, I examine the prediction of the theoretical model within multiple asset categories. The advantage of examining multiple asset categories concurrently is to increase the number of observations and consequently increase the robustness of the results. Therefore, I define the first testable hypothesis as:

1) The low-risk effect in a particular asset category is stronger in a period following stronger tournament behavior.

With this hypothesis I therefore examine the time-series relation between the low-risk premium and tournament behavior.

As the model can in fact predict multiple tournaments, I would expect that in those asset categories where managers exhibit stronger tournament behavior, the low-risk anomaly is stronger. I therefore define the second hypothesis:

2) The low-risk effect is stronger in asset categories where tournament behavior is stronger.

I refer to this hypothesis when investigating the low-risk premium and tournament behavior across asset categories.[61] In the next sessions I investigate these questions empirically.

5.4. Data low-risk premiums and tournament behavior

In this section I describe the data used in the study and the measures employed to compute tournament behavior and the low-risk premiums.

5.4.1. Tournament behavior

To measure tournament behavior I make use of the Morningstar mutual fund database with monthly returns and market values in US Dollars from January 1990 to December 2013. The study covers 12 different asset categories, consisting of bond classes, regional equity classes and style sub-classes within US equities. To obtain global coverage, I combine the funds from the Morningstar US and EAA (Europe/Africa/Asia) database, which are two separate databases containing funds depending on where these are domiciled. The databases contain funds with multiple listings and almost identical returns. To prevent a fund to dominate the final result, I only use the listing with the longest return history in the final dataset. Table 5.1 presents the total number of unique funds per asset category. In addition it presents the number of funds per category at the beginning and at the end of the sample period.

We observe large numbers of funds per asset category, where US Investment Grade Bonds contains the lowest number of funds with 124 in total and Global Equities the highest number of funds with 4,148. Furthermore, we observe a large increase in number of funds for all asset categories. A remarkable category is Emerging Markets Equities which starts with only 9 funds in January 1990 and ends with 771 funds in December 2013. The number

[61] We do not have to make assumptions of managers investing in only asset category. Theoretically, a manager (agent) can manage multiple funds and therefore invest in assets of multiple asset categories. In that case the manager can get utility from tournament behavior of more than one asset category. Alternatively, a multi-asset manager allocates assets across categories and therefore invests in multiple asset classes. In that case it is more common to allocate to index futures or specific funds then selecting individual securities within that asset class. That would imply that it is unlikely that such a manager participates in the tournaments within asset categories.

of funds in this asset category increases fast, with 100 emerging markets funds at the end of 1994 (not reported in table).

TABLE 5.1. Number of funds per asset category
The table contains the total number of funds per asset category and the number of funds in January 1990 and December 2013.

Asset class	**Number of funds**		
	Total	1990-01	2013-12
US Value Equities	916	116	401
US Blend Equities	2,167	221	950
US Growth Equities	1,372	186	614
US Mid Cap Equities	1,124	118	496
US Small Cap Equities	1,294	83	606
Global Equities	4,148	202	2,298
European Equities	1,826	73	924
Japanese Equities	842	80	332
Emerging Markets Equities	1,208	9	771
US Government Bonds	648	175	184
US Investment Grade Bonds	124	10	102
US High Yield Bonds	476	62	240

As a measure for tournament behavior, I use a test statistic in line with Brown et al. (1996) as commonly reported in academic literature. They investigate whether mid-year losers take substantially more risk than mid-year winners in the second half of the year. More specifically, each year I compute the tournament behavior in the different fund categories. To measure this behavior the funds within an asset category are ranked annually at the end of June based on their January to June returns and determine the 25 percent winner and loser funds. Accordingly, for each fund I measure the Risk Adjustment Ratio (RAR) of Brown et al. (1996) by computing the ratio of the standard deviation of the returns in the second half of the year to the standard deviation of the returns in the first half-year. I then compute the median RAR of the losers and divide by the median RAR of the winners. In case of tournament behavior we would expect this ratio to be larger than 1.

TABLE 5.2. Tournament behavior in bull and bear markets per asset category

The table contains the tournament behavior in bull and bear markets. Each year at the end of June funds within an asset category are ranked based on their January to June returns and the 25 percent winner and loser funds are computed. The Risk Adjustment Ratio (RAR) is then computed as the ratio of the standard deviation of the returns in the second half of the year to the standard deviation of the returns in the first half-year. Tournament behavior is then computed as the median RAR of the losers divided by the median RAR of the winners. The table shows the average tournament behavior split in bull and bear markets, when the market return is positive and negative, respectively, in the first half-year over the sample period January 1990 to December 2013. The last row contains the difference in tournament behavior between bull and bear markets.

	All	US Value Equity	US Blend Equity	US Growth Equity	US Mid Cap Equity	US Small Cap Equity	Global Equity	European Equity	Japanese Equity	Emerging Markets Equity	US Gov. Bonds	US IG Bonds	US HY Bonds
Bull	1.08	0.99	0.99	1.02	1.00	1.03	1.00	1.09	1.04	1.10	1.12	1.41	1.19
Bear	0.99	0.94	0.99	1.01	0.95	0.99	0.95	0.96	0.99	0.96	0.85	1.34	1.01
Bull-Bear	0.09	0.05	0.00	0.01	0.05	0.04	0.05	0.13	0.05	0.14	0.27	0.08	0.18

The average tournament behavior for each asset category is presented in Table 5.2, split in bull and bear markets, when the market return is positive and negative, respectively, in the first half-year. We observe that tournament behavior is generally present, in line with Brown et al. (1996), as the average tournament behavior statistic (median RAR losers divided by median RAR winners) is larger than 1 (1.03). However, the results clearly show that tournament behavior is time-varying and not continuously present within each asset category. In line with Kempf et al. (2009), we observe that tournament behavior is stronger when the market return is positive in the first half-year than when the market return is negative. This result holds for all asset categories, visible from the bottom line in the table where the difference in tournament behavior between bull and bear markets is presented. It is therefore important to take the time dimension into account when analyzing the relation between tournament behavior and the low-risk anomaly.

5.4.2. Low-risk premiums

To link tournament behavior to the low-risk anomaly, historical low-risk premiums of the relevant asset categories are required. In spirit of Frazzini and Pedersen (2014), I construct leveraged low-minus-high risk portfolios based on the past year volatility of individual securities (top and bottom one-third) for each of the asset categories. For government bonds I use the returns of short minus long duration bonds (1-3 years versus 7-10 years).[62]

Table 5.3 shows that the low-risk anomaly is present in almost all asset categories, consistent with Frazzini and Pedersen (2014). Only for US High Yield Bonds we observe a slightly negative low-risk period over the whole sample. We observe the largest low-risk premium for US Small Cap Equities with a Sharpe ratio of 1.05. Additionally, we see strong differences over the two sub-samples, as for example, Japanese and Emerging Markets Equities have negative low-risk premiums in the first sample period, while positive low-risk premiums in the second part of the sample period.

[62] For government bonds we construct low-minus-high risk portfolios based on the maturity of bonds. For the other asset categories we use as a proxy for the low-risk anomaly the low-volatility effect. The low-risk effect refers to both low-beta and low-volatility. The returns of the low-beta and low-volatility effects are highly correlated. The difference is that correlations with the market are not taken into account for the low-volatility effect. The reason to use volatility instead of the beta as a measure are twofold: 1) An advantage of the low-volatility measure is that no (arbitrary) benchmark needs to be assumed and 2) there are studies that find the low-volatility effect to be stronger than the low-beta effect [e.g. Blitz and van Vliet (2007) and Cederburg and O'Doherty (2016)].

TABLE 5.3. Low-risk premiums per asset category

The table contains low-risk premiums in different asset categories over the whole sample period from 1990 to 2013 and over two sub-samples, from 1990 to 2001 and from 2002 to 2013. For each of the asset categories leveraged low-minus-high risk portfolios are constructed based on the past year volatility of individual securities (top and bottom one-third) For government bonds I use the returns of short minus long duration bonds (1-3 years versus 7-10 years).

	US Value Equity	US Blend Equity	US Growth Equity	US Mid Cap Equity	US Small Cap Equity	Global Equity	European Equity	Japanese Equity	Emerging Markets Equity	US Gov. Bonds	US IG Bonds	US HY Bonds
1990-2013												
Excess return	3.83%	6.62%	7.00%	12.86%	19.04%	5.36%	6.16%	0.06%	1.61%	0.91%	0.55%	-0.15%
Volatility	10.38%	14.68%	16.49%	15.61%	18.12%	11.26%	9.35%	11.06%	14.01%	1.86%	2.44%	9.27%
Sharpe Ratio	0.37	0.45	0.42	0.82	1.05	0.48	0.66	0.01	0.12	0.49	0.22	-0.02
1990-2001												
Excess return	3.77%	6.17%	6.49%	14.22%	26.56%	3.91%	5.10%	-3.88%	-6.23%	1.60%	0.83%	1.74%
Volatility	11.89%	18.44%	19.95%	17.62%	18.89%	13.46%	9.88%	11.52%	17.39%	1.52%	1.20%	11.10%
Sharpe Ratio	0.32	0.33	0.33	0.81	1.41	0.29	0.52	-0.34	-0.36	1.06	0.69	0.16
2002-2013												
Excess return	3.90%	7.08%	7.51%	11.51%	11.97%	6.83%	7.24%	4.17%	10.11%	0.21%	0.27%	-2.01%
Volatility	8.64%	9.60%	12.16%	13.35%	17.19%	8.54%	8.82%	10.50%	9.05%	2.14%	3.24%	6.98%
Sharpe Ratio	0.45	0.74	0.62	0.86	0.70	0.80	0.82	0.40	1.12	0.10	0.08	-0.29

Furthermore, we observe that the volatility of the low-risk premiums can differ significantly. Although in terms of Sharpe ratio, the low-risk premium of Global Equities and US Government Bonds are equal, the low-risk premium is almost six times higher for Global Equities obviously because the equity premium has also been higher than the bond premium. Finally, we observe a low correlation of 0.28 among the low-risk return series of different asset categories. Due to this finding it is unlikely that a global risk factor which is non-asset class specific, such as TED-spread and inflation, can fully explain the low-risk anomaly, as used by Frazzini and Pedersen (2014) and Cohen et al. (2005), respectively.

5.5. The low-risk anomaly and tournament behavior

In the following analyses, I empirically investigate the relation between tournament behavior and the low-risk premium. It starts with the first hypothesis where I investigate whether, for a particular asset category, the low-risk effect is stronger in a period following stronger tournament behavior. It follows in Sub-sections 5.5.2 and 5.5.3 where I empirically test the second hypothesis to determine whether the low-risk effect is stronger in asset categories where tournament behavior is stronger.

5.5.1. The time-series relation

To investigate whether for a particular asset class, the low-risk effect is stronger in a period following stronger tournament behavior, I start the empirical analyses with pooled OLS regressions on multiple asset categories. The advantage of examining multiple asset categories simultaneously is that it increases the number of observations and it allows to assess the robustness of the results. From Table 5.2 we saw that the volatility of the low-risk premiums differs significantly across asset categories. To prevent risky asset categories (such as US Small Cap Equites) to dominate the results and asset categories with a low-risk (such as US Government Bonds) to have little impact, I standardize the low-risk premiums of the asset categories based on their own sample histories. The pooled OLS regressions are specified as follows:

(5.22) $$Zr_{i,t} = c_t + b_t ZRARLosWin_{i,t-1} + \varepsilon_{i,t}.$$

In this equation Z$r_{i,t}$ is the low-risk premium of asset category *i* in year *t* where I standardize the low-risk premium by subtracting the asset category's sample median annual low-risk premium and divide by the asset category's sample median standard deviation. This ensures comparability of the low-risk premium across asset categories. $ZRARLosWin_{i,t}$ is the time-series standardized tournament behavior in asset category i in year t, where tournament behavior is standardized by subtracting the average tournament behavior of that asset category and dividing by the asset category's historical standard deviation of tournament behavior. This standardization again ensures a time-series comparison. Table 5.4 shows the regression coefficients and the associated t-statistics. In addition, I present the adjusted R-squared values. I perform the regression on all data points in the complete sample and also split the sample in the two sub-periods 1990 to 2002 and 2003 to 2013 to investigate the robustness of the results.

We observe a positive and significant relation between tournament behavior and the low-risk premium with a t-statistic of 2.93. When we consider the last two columns in the table, we observe that the relation is also positive and significant in both sub-periods. I therefore conclude that there is a positive relation between tournament behavior and the low-risk premium over time.

TABLE 5.4. Pooled OLS-regression results for the relation between low-risk premium and tournament behavior across time

This table reports pooled OLS-regression results of low-risk premiums regressed on tournament behavior over the period January 1990 until December 2013 and over the two sub-periods 1990 to 2002 and 2003 to 2013:

(5.22) $$Zr_{i,t} = c_t + b_t ZRARLosWin_{i,t-1} + \varepsilon_{i,t}.$$

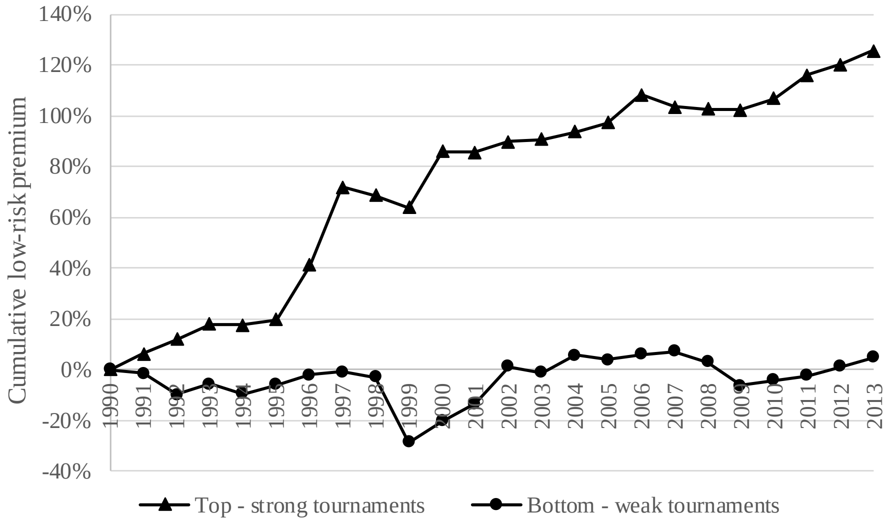
where $Zr_{i,t}$ is the low-risk premium of asset category i in year t where I standardize the low-risk premium by subtracting the asset category's sample median annual low-risk premium and divide by the sample median standard deviation. $ZRARLosWin_{i,t}$ is the time-series standardized tournament behavior in asset category i in year t, where tournament behavior is standardized by subtracting the average tournament behavior of that asset category and dividing by the asset category's historical standard deviation of tournament behavior. The table presents the average coefficient estimates of the different time periods together with their t-values (second row). In addition, the table shows the R-squared values of the regressions.

	1990-2013	1990-2002	2003-2013
Constant	-0.02	0.16	-0.22
	-0.27	1.32	-2.09
ZRARLosWin	0.24	0.21	0.33
	2.93	2.01	2.26
R2	3.0%	2.8%	3.8%

5.5.2. Across asset categories

In this subsection and the following I focus on the second hypothesis based on the theoretical model, namely a cross-sectional comparison of tournament behavior and the low-risk premiums. So far, the empirical analysis showed a positive relationship between tournament behavior and the low-risk premiums across time, in line with the first hypothesis. Is there also a positive relation between tournament behavior and the low-risk premium across asset categories? I therefore continue the empirical analyses with a sorting test. Based on their tournament behavior I sort the asset categories in groups and investigate their low-risk premiums. More specifically, each year the asset categories are sorted into terciles based on their tournament behavior in that year. For the three resulting groups each containing 4 asset categories, I compute the low-risk premium over the subsequent year. Because of the differences in volatility of the low-risk premiums across asset categories, I compute risk-weighted low-risk premiums of each group, where the weights are proportional to the inverse of the sample standard deviation of the low-risk premiums of the asset categories. The results are presented in Figure 5.6.

FIGURE 5.6. Cumulative low-risk returns of an investment strategy based on tournament behavior
Cumulative log low-risk returns of top and bottom tercile portfolios of asset categories with the strongest and weakest tournament behavior, respectively. Each year over the period 1990 to 2013, the asset categories are sorted into terciles based on their tournament behavior in that year. Next, for the three resulting groups, the low-risk premium over the subsequent year is computed. The weights of the asset categories are proportional to the inverse of the historical standard deviation of the asset categories' low-risk premiums.



We observe a positive relation between tournament behavior and the low-risk premium. The tercile group with the strongest tournament behavior performs significantly better than the group with the weakest tournament behavior. In 17 out of the 23 calendar years, the top terciles group (strong tournament behavior) outperforms the bottom portfolio (weak tournament behavior). The asset categories with the weakest tournament behavior earned a low-risk premium of around 0%; in other words, the low-risk premium is not present for the asset categories where tournament behavior is weakest.

TABLE 5.5. Long-short investment strategy of the low-risk premium based on tournament behavior

Panel A shows the results of an investment strategy where each year I take 100% long (short) positions in the low-volatility strategy of the one-third asset categories with the strongest (weakest) tournament behavior. Weights are inverse to the volatility of the low-risk premiums in that asset category. Sample period: 1990-2013. The timing benchmark is based on fixed weights per asset category, where I average the weights of each asset category in the long/short strategy over the whole sample period. Panel B shows the results of the investment strategy corrected for loadings to a set of market indices. Second row contains *t*-statistics.

	Strategy	Strategy -/- timing benchmark	Timing benchmark
Panel A. Return statistics investment strategy			
Excess return	5.09%	5.18%	-0.08%
Standard deviation	10.21%	10.34%	1.06%
Sharpe ratio	0.50	0.50	-0.08
t -statistic	2.39	2.40	-0.38
Panel B. Strategy return corrected for market factors			
Constant	7.05%		
	2.23		
Equities	0.01		
	0.05		
GovBonds	-0.70		
	-1.10		
HYBonds	0.01		
	0.06		
Adj. R2	9.1%		

Continuing the analyses further, I consider the low-risk premium statistics of the top-minus-bottom tercile portfolio of Figure 5.6. In other words, each year we take 100% long (short) positions in the low-volatility strategy of the one-third asset categories with the strongest (weakest) tournament behavior. Weights are inverse to the volatility of the low-risk premiums in that asset category. Panel A of Table 5.5 presents the annualized excess low-risk premium of the strategy, together with the associated annual standard deviation, Sharpe ratio and *t*-statistic. We observe strong and significant returns of on average around 5% per annum with a *t*-statistic of 2.39.

Next, I investigate whether the positive relation between tournament behavior and the low-risk premiums are driven by the structural positions in particular asset categories that have done very well over this sample period. For that, I construct a so-called timing benchmark which is based on fixed weights per asset category, where I use the average weight of each asset category in the long/short strategy over the whole sample period. I then compute the return of this timing benchmark. Panel A of Table 5.5 shows that the timing benchmark (column 3) has performed poorly with an average return just below zero. This means that the results of the investment strategy compared to this timing benchmark remain very similar with 5.18% per annum. We can therefore conclude that the positive relation between tournament behavior and the low-risk premiums cannot be attributed due to structural positions in particular asset categories.

Proceeding, I perform a multiple regression of the investment strategy returns on general market returns to investigate if the magnitude of the returns is affected by exposures to these market returns. For purposes thereof, I estimate the following regression equation:

$$\text{(5.23)} \qquad R_{TMB,t} = \alpha + \beta_{Equities} R_{Equities,t} + \beta_{GovBonds} R_{GovBonds,t} + \beta_{HYBonds} R_{HYBonds,t} + \varepsilon_t$$

where $R_{TMB,t}$ is the low-risk premium of the top-minus-bottom tercile portfolio, $R_{Equities,t}$ is the return of global equities, proxied by the equally-weighted returns of the largest 2,800 stocks each month of the S&P Developed Broad Market Index, $R_{GovBonds,t}$ is the return of US government bonds (1-10 years, Datastream) in excess of the repo rate and $R_{HYBonds,t}$ is the return of US High Yield Bonds (Barclays) in excess of US government bonds. An alpha statistically different from zero implies that the excess returns of the investment strategy cannot be explained by general market factors.

When we consider the coefficient estimates of the regression in Panel B of Table 5.5, we observe a low-risk premium of the investment strategy, which is even somewhat higher after correcting for exposures to general market indices. Moreover, we observe no significant exposures to the three market indices. So, the positive relation between tournament behavior and the low-risk premiums remains or even becomes somewhat stronger when corrected for loadings to general market returns or structural positions.

5.5.3. Corrected for other effects

To further investigate the impact of tournament behavior on the low-risk premiums as described with the second hypothesis, I next perform cross-sectional Fama and MacBeth (1973) regressions. The advantage of this method is that we can easily control for multiple other effects that might have impact on the relationship between tournament behavior and the low-risk premium. Therefore, I yearly regress the low-risk premiums on tournament behavior and other factors in the prior year that could potentially influence the results:

$$Zr_{i,t} = c_t + b1_t RARLosWin_{i,t-1} + b2_t ControlVar_{i,t-1} + \varepsilon_{i,t}. \quad (5.24)$$

$Zr_{i,t}$ is again the standardized low-risk premium of asset category i in year t. The variable $RARLosWin_{i,t}$ is the tournament behavior in asset category i in year t and $ControlVar_{i,t}$ is a control variable for asset category i in year t.

I investigate four control variables. First, I control for the activeness of the market. The idea here is that the larger the mutual fund market of a particular asset category, the larger the low-risk premium. In case of strong tournament behavior in an asset category, but a relatively small mutual fund market, the impact on asset prices will likely be low. I use two proxies for the activeness of the market in year t: 1) *NFunds*, which is the number of mutual funds in a particular asset category and 2) *PercMCap*, which is the ratio of the total net market value of the mutual funds in an asset category divided by the total market value of that asset category.[63] I proxy the latter by the total market cap of the individual securities in the universe of that asset category which I use to compute the low-risk premium. Second, I control for the relative market volatility over the past 12 months *ZMarketVol*, which I standardize by subtracting the sample mean of that asset category and divide it by its standard deviation. This makes volatility comparable across asset categories. The reason to include this variable is to investigate whether selecting relatively low-volatile asset categories could drive the higher low-risk premium. Last, I use the return-to-risk ratio of the

[63] The market value data of mutual funds in the Morningstar database are often not continues series. In case of a missing observation I take the last available market value in case of less than a year missing market values.

market of the asset category each year, labelled *MarketReturnRisk*. The idea is to investigate whether asset categories that have performed well are also the asset categories with a high low-risk premium. Table 5.6 presents the average coefficient estimates of the different regression models together with the associated *t*-values which are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). Additionally, the table presents the average adjusted R-squared values of the regressions.

The resulting coefficient estimates of the base case regression in column (1) show a large and significant coefficient for tournament behavior. Columns (2) to (5) of Table 5.6 show the coefficient estimates when we augment the base case regression model with each of the four control variables. If the positive relation between tournament behavior and the low-risk premiums can be attributed to control variables, we should observe that augmenting the cross-sectional regressions of the low-risk anomaly on tournament behavior with control variables should lead to a significant decrease of the estimated coefficient of tournament behavior. In addition we should observe that the coefficient estimates of the control variables become significant. However, in almost all cases we observe that the coefficient estimate for *RARLosWin* remains significant and nearly unchanged. Only when controlling for market volatility we observe a lower *t*-statistic for tournament behavior. Moreover, apart from market volatility, none of the coefficient estimates for the control variables turns out significantly different from zero. The reason that the two proxies for the activeness of the market do not show up significantly, could be because I use only large and relevant asset categories, which have a relatively large mutual fund market.

The last row of the table shows the adjusted R-squared values. From the first column we observe that tournament behavior explains 8.90% of the variability of the low-risk premiums. We observe a moderate increase in explanatory power once control variables are added to the regression. When market volatility is added, the explanatory power increases to 12.20% (column 4). This means that still the majority of the variation is explained by tournament behavior. In case the return-to-risk ratio of the asset categories is added, we observe that the R-squared value increases to 17.80% (column 5), which is double that of the base case regression. This seems to suggest that the risk-return ratio of the categories can explain part of the variability of the low-risk premiums. However, the estimation coefficient shows that the relation between this control variable and tournament behavior is not statistically significant, while tournament behavior remains statistically significant.

TABLE 5.6. Fama-MacBeth regression results for the relation between low-risk premium and tournament behavior across asset categories

This table reports Fama-MacBeth regression results of low-risk premiums regressed on tournament behavior while controlling for other effects over the period January 1990 until December 2013. Each year the following regression is performed:

(5.24) $$Zr_{i,t} = c_t + b1_t RARLosWin_{i,t-1} + b2_t ControlVar_{i,t-1} + \varepsilon_{i,t},$$

where $Zr_{i,t}$ is the low-risk premium of asset category *i* in year *t* where I standardize the low-risk premium by subtracting the asset category's sample median annual low-risk premium and divide by the sample median standard deviation. The variable $RARLosWin_{i,t}$ is the tournament behavior in asset category *i* in year *t*. The base case regression in Equation 5.24 is augmented with four control variables $ControlVar_{i,t}$ for asset category *i* in year *t*. The four control variables: *NFunds* is the number of mutual funds in a particular asset category; *PercMCap* is the ratio of the total net market value of the mutual funds in an asset category divided by the total market value of that asset category; *ZMarketVol* is the relative market volatility over the past 12 months standardized by subtracting the sample mean of that asset category and divide by the standard deviation; *MarketReturnRisk* is the return-to-risk ratio of the market of the asset category each year. The table presents the average coefficient estimates of the different regression models together with their *t*-values (second row) computed using Newey-West (1987) standard errors. In addition, the table shows the average adjusted R-squared values of the regressions.

	(1)	(2)	(3)	(3)	(5)
Constant	-1.21	-1.26	-1.29	-1.09	-0.90
	-2.12	-1.78	-2.11	-1.64	-1.86
RARLosWin	1.23	1.26	1.28	1.14	0.92
	2.49	2.01	2.31	1.83	2.16
Nfunds		0.00			
		0.25			
PercMcap			0.08		
			0.95		
ZMarketVol				-0.38	
				-3.23	
MarketReturnRisk					0.06
					0.66
Adj. R2	8.90%	11.90%	9.10%	12.20%	17.80%

All in all, the outcomes of the Fama-MacBeth regressions are consistent with the results based on the sorting test of the previous sub-section. It appears that the finding that the low-risk premium is positive related to tournament behavior is robust to the method that is used to investigate the relation between the two variables. Moreover, the relation is not affected by the activeness of the market, market volatility and risk-return ratio of the market.

I therefore conclude that there is also a positive relation between tournament behavior and the low-risk premium over the cross-section.

5.6. Extensions and further discussions

The theoretical model I present in this study together with the empirical analyses show that tournament behavior can go a long way towards explaining the low-risk anomaly. In this section I discuss several possibilities to extend the general equilibrium model.

5.6.1. Tournament behavior and the type of market

Although a vast amount of literature demonstrates the existence of tournament behavior across mutual funds, Kempf et al. (2009) argue that it is dependent on the market return in the first half-year. More specifically, they show that tournament behavior exists when the first half-year is a bull market and not when it is a bear market. They relate this to the relative importance of compensation and employment incentives. The authors argue that employment risk is more important than compensation incentives after bear markets. The study shows that fund managers with a poor midyear performance tend to decrease risk relative to leading managers after bear markets to prevent potential job loss (weak tournament behavior). Contrary, employment risk is low after bull markets and compensation incentives become more relevant. Accordingly, they find that fund managers with a poor midyear performance increase risk to catch up with the midyear winners after bear markets (strong tournament behavior). As mutual fund investors chase returns over time, these compensation incentives become stronger after bull markets. This would imply strong tournament behavior and higher low-risk premiums after bull markets, while weaker tournament behavior and lower low-risk premiums after bear markets.

If we return to the theoretical model of Section 5.3 then Equation 5.14 presents the utility function extended with tournament behavior, where η is the parameter that indicates the sensitivity towards tournament behavior:

$$(5.14) \qquad \max_{q_{AH},q_{AL}} E\left[-\exp\left(-\theta_A(W_{A1}-W_{A0})\right)+\eta_A(R_A-R_B)\right].$$

An extension of the model would be to let the parameter η depend on the type of market, based on the findings of Kempf et al. So, giving it a higher value after bull markets, indicating an increased sensitivity to tournament behavior after bull markets. The difficulty for agents is to forecast whether the coming period will be a bear or a bull market and to adjust their behavior accordingly.

Table 5.1 already showed that in line with Kempf et al., tournament behavior is stronger when the market return is positive in the first half-year than when the market return is negative. We could next investigate whether this is also associated more often with a positive low-risk premium. For that I construct so-called 2x2 contingency tables of tournament behavior and the low-risk premium based on all 276 observations (12 asset categories times 23 calendar years). I divide the observations in high and low tournament behavior (*RARLosWin*) where I use the median *RARLosWin* of the sample as a cut-off point. Furthermore, I also split the observations in a high or low low-risk premium segment depending on whether the standardized low-risk premium is larger or smaller than the median value (which is zero), respectively. Moreover, I perform the same analysis, but then based on the observations for which there was a bull market (positive market return) or bear market (negative market return) in the first half-year. The null hypothesis in these tests is that the percentage of observations falling into each of the four cells is equal to the expected values, which implies that the tournament behavior and the low-risk premium are independent. The alternative hypothesis, in case tournament behavior is positively related to the low-risk premium, is that the 'high tournament behavior/high low-risk premium' and 'low tournament behavior/low low-risk premium' would have larger frequencies than the other two outcomes. I test the significance of the frequencies with a chi-square test. The percentage of the observations of each segment are presented in Table 5.7, together with the χ^2 test statistics and the associated *p*-values.

TABLE 5.7. Contingency tables of tournament behavior and the low-risk premiums

The contingency table reports the percentage of sample observations when these are split in high and low tournament behavior (*RARLosWin*) based on the median *RARLosWin* of the sample as cut-off point and in a high or low low-risk premium segment depending on whether the standardized low-risk premium is larger or smaller than the median value, respectively. The table shows the outcome on all sample observations and in addition on the observations for which there was a bull market (positive market return) or bear market (negative market return) in the first half-year. The table presents the total number of observations and the chi-squared test-statistic with its associated *p*-value.

		High *RARLosWin*		Low *RARLosWin*			
	Observations	High premium	Low premium	High premium	Low premium	χ^2	*p*-value
All	276	**30.07%**	19.93%	22.10%	**27.90%**	7.03	0.008
Bull	197	**32.49%**	20.81%	22.34%	24.37%	3.41	0.065
Bear	79	24.05%	18.00%	22.00%	**37.00%**	3.29	0.070

In case of no relation between tournament behavior and the low-risk anomaly, we would expect 26.1% of the observations in each of the 'high low-risk premium' segments and 23.9% in each of the 'low low-risk premium' segments and no significant deviations from these numbers.[64] However, we observe most observations and much more than expected in the entire sample fall in the 'high tournament behavior/high low-risk premium' and 'low tournament behavior/low low-risk premium' segments. More specifically, we observe 58.0% of the observations in these two segments versus 42.0% in the 'high tournament behavior/low low-risk premium' and 'low tournament behavior/high low-risk premium' segments. This finding is in line with earlier results where I show a positive relation between tournament behavior and the low-risk premium. The chi-squared test statistic and associated *p*-value show that these values are statistically significantly different from their expected values.

Interestingly, during bull markets we observe most observations in the 'high tournament behavior/high low-risk premium' segment and during bear markets in the 'low tournament behavior/low low-risk premium' segment. These findings are in line with the hypothesis that mutual fund manager's incentives to perform well are strongest during bull markets.

5.6.2. Investment horizon

Up to now, I have empirically investigated the link between tournament behavior in year *t*-1 and low-risk premiums in year *t*. This is in line with the general equilibrium model from Section 5.3 where tournament behavior at time *t*-1 is linked to the returns of the asset from time *t*-1 to time *t*. However, tournament behavior cannot be measured at one particular moment in time. I measure it over a calendar year in line with Brown et al. (1996). Accordingly, I measure the return over the next year. Intuitively, this is a logical choice, as the tournaments also follow an annual frequency. However, the choice for the length of the period to measure the low-risk premium can be made dependent on the investment horizon of the investor, which is not known beforehand. I therefore investigate in this sub-section the relationship between tournament behavior and the low-risk premium, where the low-risk premium is measured over a 2- and 3-years horizon as well. I expect the relation to be weaker

[64] I compute these expected values based on the number of observations of the four groups independently. E.g. 138 of the 276 observations are defined as high *RARLosWin* and 144 of the 176 observations are defined as high low-risk premium. Then, in case of independence, we would expect 138/276*144=26.1% of the observations in the 'high tournament behavior/high low-risk premium' segment.

when the low-risk premium is measured over a longer time period, as new tournaments have already started.

TABLE 5.8. Relation between low-risk premium and tournament behavior across asset categories with different investment horizons

Panel A reports pooled OLS-regression results of low-risk premiums regressed on tournament behavior:

(5.22) $Zr_{i,t} = c_t + b_t ZRARLosWin_{i,t-1} + \varepsilon_{i,t}$.

where $Zr_{i,t}$ is the low-risk premium of asset category *i* in year *t*, year *t* to *t+1* and year *t* to *t+2*, where the low-risk premium is standardized by subtracting the asset category's sample median and divide by the sample median standard deviation. $ZRARLosWin_{i,t}$ is the time-series standardized tournament behavior in asset category *i* in year *t*, where tournament behavior is standardized by subtracting the average tournament behavior of that asset category and dividing by the asset category's historical standard deviation of tournament behavior.

Panel B reports Fama-MacBeth regression results of low-risk premiums regressed on tournament behavior. Each year the following regression is performed:

(5.24) $Zr_{i,t} = c_t + b1_t RARLosWin_{i,t-1} + \varepsilon_{i,t}$,

where $Zr_{i,t}$ is the low-risk premium of asset category *i* in year *t*, year *t* to *t+1* and year *t* to *t+2*. The variable $RARLosWin_{i,t}$ is the tournament behavior in asset category *i* in year *t*. The table presents the coefficient estimates together with their *t*-values (second row) over the sample period January 1990 until December 2013. In addition, the table shows the R-squared values of the regressions.

Investment horizon	1 year	2 years	3 years
Panel A. Time-series			
Constant	-0.02	-0.05	0.04
	-0.27	-0.60	0.42
ZRARLosWin	0.24	0.19	0.01
	2.93	2.45	0.08
R2	3.00%	2.24%	0.00%
Panel B. Cross-sectional			
Constant	-1.21	-0.73	-1.02
	-2.12	-1.31	-0.77
RARLosWin	1.23	0.74	1.15
	2.49	1.68	1.00
Adj. R2	8.90%	8.87%	16.27%

For that purpose, I repeat the analyses from Table 5.4 and Table 5.6 for the base case test. Table 5.4 showed the results of the time-series relation between the low-risk premium and tournament behavior based on pooled OLS regressions. I now perform the same analysis, where I compute the low-risk premium on a 2-years and 3-years horizon as well, besides the 1-year horizon. Results are presented in Panel A of Table 5.8.

From the table we observe still a positive and significant relationship between tournament behavior and the low-risk anomaly when the low-risk premiums are measured on a 2-years horizon. However, the coefficient and associated *t*-statistic are somewhat lower, in line with expectations. On a 3-years horizon, the relation is weak and insignificant.

I next present the results of cross-sectional analyses to the relation between tournament behavior and the low-risk premium, as shown in Table 5.6. Again I compute the low-risk premium on a 2-years and 3-years horizon as well. Results are presented in Panel B of Table 5.8. We observe a similar effect as in Panel A. The results become weaker and insignificant when I increase the length of the period to compute the low-risk premium. The results imply that tournaments have most impact on the prices of low- and high-risk asset in the year following the tournaments. This could be caused by new tournaments that have started where the 'newest' high-risk stocks are being selected and for which the demand is higher than the 'older' high-risk stocks.

5.6.3. Other extensions

There are several other interesting research areas to extend the presented theoretical model, which are beyond the scope of this study. One is to extend the model to a two-period, and therefore multi-period, model. The advantage is that the high-risk asset will not always be the same asset, but that this can change through time, which makes the model more general. My expectation is that the outcome of the model will remain the same. In other words, tournament behavior will decrease the expected return of the high-risk asset. However, this needs to investigated further in follow-up research.

Another extension is to increase the number of agents in the model. The advantage of more agents is that there is less impact of a single agent on the market price. In case of two agents, if one agent wants to buy asset A and sell asset B, the other agent will only buy asset B in case the price is low enough. With more agents, the effect on prices are expected to be lower. In a model with more than two agents, it would be interesting to analyze the shape of the security market line again, as presented in Figure 5.3. This could potentially lead not only to a flatter, but also to an inverse shape of the security market line.

A different angle to the model would be to extend it with a risk-free asset. If leverage is unrestricted and cheap, taking more leverage is also a way to increase risk. This could mean that shorting the risk-free rate and buying the low-risk asset might also become an attractive alternative to increase the risk-profile of the portfolio in case of tournament behavior. In that case we would expect a somewhat lower impact of tournament behavior on the prices of low-risk assets. I would also expect a less strong relation between tournament behavior and the low-risk premiums in case an agent would short the high-risk asset. In the current model that is already possible. However, it could be that the limitation to two assets, limits the possibilities for the agents to do so, as the price of the high-risk asset must be so attractive for the other agent to buy it. However, if leverage is restricted and/or costly, high-risk securities become more attractive and fund managers are prepared to pay a premium which decreases the return on these high-risk securities. In the real world there are however restrictions on leverage. For many mutual funds leverage is not allowed.[65] If leverage is limited and all fund managers would use the allowed amount of leverage, then again the way to take more risk, is to buy high-risk assets. Moreover, leveraging is not for free, which also pushes fund managers in the direction of buying high-risk asset instead of taking more leverage (in case that is allowed).

5.7. Concluding remarks

Due to the large shift of assets from individual investors to fund managers over the past decades, the impact of these managers' behavior on asset prices has grown. A large stream of literature has been developed on an important behavior characteristic of these intermediaries, namely tournament behavior. In this study I show that this behavior is an important driver in explaining one of the most important asset pricing anomalies: the low-risk premium. The academic literature is inconclusive on why this anomaly exists, as not many studies examined the cause of this anomaly. This study contributes to the literature in many aspects.

First, the general equilibrium model I developed shows that tournament behavior causes the securities market line to be flatter than expected according to the CAPM. Second, the empirical analyses across different asset categories confirm this positive relationship between tournament behavior and the low-risk returns. The results indicate that not only the low-risk effect is more prominent in a period following stronger tournament behavior, but also that the anomaly is larger in asset categories where more tournament behavior is observed. Irrespective of whether I use panel OLS-regressions, a sorting approach, Fama and MacBeth (1973) analyses or contingency tables, I find that the low-risk premium can be attributed to tournament behavior.

[65] For example, European UCITS funds are not allowed to take physical short positions in individual stocks and can only take limited short positions in futures. Source www.esma.europa.eu.

The finding of a positive relationship between tournament behavior and the low-risk premiums helps to explain the low-risk anomaly across a wide range of asset classes. I acknowledge that other explanations could strengthen this effect. For example, leverage and shorting restrictions could intensify the positive relation between tournament behavior and the low-risk premium, which would be an interesting direction for follow-up research.

5.A. Solving the model with tournament behavior

In this appendix I solve the maximization problem with tournament behavior for agent A:

(5.15) $\max_{q_{AH},q_{AL}} E[-\exp(-\theta_A\{q_{AH}(D_{H1}-P_{H0})+q_{AL}(D_{L1}-P_{L0})\})+\eta_A(w_{AH}R_{H1}+w_{AL}R_{L1}-w_{BH}R_{H1}-w_{BL}R_{L1})]$,

We can further write Equation 5.15 as:

(5.25) $$\max_{q_{AH},q_{AL}} E[-\exp(-\theta_A\{q_{AH}(D_{H1}-P_{H0})+q_{AL}(D_{L1}-P_{L0})\})+\eta_A(w_{AH}R_{H1}+w_{AL}R_{L1}-w_{BH}R_{H1}-w_{BL}R_{L1})]$$

$$=\max_{q_{AH},q_{AL}} E\Bigg[-\exp(-\theta_A\{q_{AH}(D_{H1}-P_{H0})+q_{AL}(D_{L1}-P_{L0})\})+\eta_A\left(\frac{q_{AH}P_{H0}}{q_{AH}P_{H0}+q_{AL}P_{L0}}\left(\frac{D_{H1}}{P_{H0}}-1\right)+\frac{q_{AL}P_{L0}}{q_{AH}P_{H0}+q_{AL}P_{L0}}\left(\frac{D_{L1}}{P_{L0}}-1\right)-\frac{q_{BH}P_{H0}}{q_{BH}P_{H0}+q_{BL}P_{L0}}\left(\frac{D_{H1}}{P_{H0}}-1\right)-\frac{q_{BL}P_{L0}}{q_{BH}P_{H0}+q_{BL}P_{L0}}\left(\frac{D_{L1}}{P_{L0}}-1\right)\right)\Bigg]$$

$$=\max_{q_{AH},q_{AL}} F+\frac{\eta_A(\mu-P_{H0})q_{AH}+\eta_A(\mu-P_{L0})q_{AL}}{q_{AH}P_{H0}+q_{AL}P_{L0}}-\frac{\eta_A(\mu-P_{H0})q_{BH}-\eta_A(\mu-P_{L0})q_{BL}}{q_{BH}P_{H0}+q_{BL}P_{L0}}$$

where $F=-\exp(-\theta_A\{q_{AH}+q_{AL}\}\mu+\theta_A q_{AH}P_{H0}+\theta_A q_{AL}P_{L0}+\frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2+q_{AL}^2\sigma_L^2+2\rho q_{AH}q_{AL}\sigma_H\sigma_L\})$ from Equation 5.6.

Then the first order condition of agent A for asset H is given by:

(5.26) $$F*G+\frac{\eta_A(\mu-P_{H0})(q_{AH}P_{H0}+q_{AL}P_{L0})-P_{H0}\eta_A(\mu-P_{H0})q_{AH}-P_{H0}\eta_A(\mu-P_{L0})q_{AL}}{(q_{AH}P_{H0}+q_{AL}P_{L0})^2}=0$$

where $G=-\theta_A\mu+\theta_A P_{H0}+\theta_A^2 q_{AH}\sigma_H^2+\theta_A^2\rho q_{AL}\sigma_H\sigma_L$. Solving Equation 5.26 leads to:

(5.27) $$F*G+\frac{\eta_A(\mu-P_{H0})q_{AL}P_{L0}-\eta_A(\mu-P_{L0})q_{AL}P_{H0}}{q_{AH}^2P_{H0}^2+2q_{AH}P_{H0}q_{AL}P_{L0}+q_{AL}^2P_{L0}^2}=0$$

The full equation is then:

(5.16)

$$
\begin{aligned}
&-\exp\Big(-\theta_A\{q_{AH}+q_{AL}\}\mu+\theta_A q_{AH}P_{H0}+\theta_A q_{AL}P_{L0}\\
&+\frac{1}{2}\theta_A^2\{q_{AH}^2\sigma_H^2+q_{AL}^2\sigma_L^2+2\rho q_{AH}q_{AL}\sigma_H\sigma_L\}\Big)*(-\theta_A\mu+\theta_A P_{H0}+\theta_A^2 q_{AH}\sigma_H^2\\
&+\theta_A^2\rho q_{AL}\sigma_H\sigma_L)\\
&+\frac{\eta_A(\mu-P_{H0})(q_{AH}P_{H0}+q_{AL}P_{L0})-P_{H0}\eta_A(\mu-P_{H0})q_{AH}-P_{H0}\eta_A(\mu-P_{L0})q_{AL}}{(q_{AH}P_{H0}+q_{AL}P_{L0})^2}\\
&=0
\end{aligned}
$$

5.B. CAPM-beta

The CAPM-beta is defined as:

(5.20) $\beta_{H,M} = \frac{cov(R_{H1},R_{M1})}{var(R_{M1})}$, where

(5.28)
$$\begin{aligned} cov(R_{H1}, R_{M1}) &= cov(R_{H1}, w_L R_{L1} + w_H R_{H1}) = w_L cov(R_{H1}, R_{L1}) + w_H var(R_{H1}) \\ &= w_L cov\left(\frac{D_{H1}}{P_{H0}}, \frac{D_{L1}}{P_{L0}}\right) + w_H var\left(\frac{D_{H1}}{P_{H0}}\right) \\ &= w_L \frac{1}{P_{H0}P_{L0}} cov(D_{H1}, D_{L1}) + w_H \frac{\sigma_H^2}{P_{H0}^2} = w_L \frac{\rho\sigma_H\sigma_L}{P_{H0}P_{L0}} + w_H \frac{\sigma_H^2}{P_{H0}^2} \end{aligned}$$

and

(5.29)
$$\begin{aligned} var(R_{M1}) &= var(w_H R_{H1} + w_L R_{L1}) \\ &= w_H^2 var(R_{H1}) + w_L^2 var(R_{L1}) + 2 w_L w_H cov(R_{H1}, R_{L1}) \\ &= w_H^2 \frac{\sigma_H^2}{P_{H0}^2} + w_L^2 \frac{\sigma_L^2}{P_{L0}^2} + 2 w_L w_H \frac{\rho\sigma_H\sigma_L}{P_{H0}P_{L0}} \end{aligned}$$

If we fill in Equations 5.28 and 5.29 in Equation 5.20, we get:

(5.30) $\beta_{H,M} = \frac{cov(R_{H1},R_{M1})}{var(R_{M1})} = \frac{w_L \frac{\rho\sigma_H\sigma_L}{P_{H0}P_{L0}} + w_H \frac{\sigma_H^2}{P_H^2}}{w_H^2 \frac{\sigma_H^2}{P_{H0}^2} + w_L^2 \frac{\sigma_L^2}{P_{L0}^2} + 2 w_L w_H \frac{\rho\sigma_H\sigma_L}{P_{H0}P_{L0}}}$

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Summary

This dissertation discusses possible explanations of anomalies in financial markets: empirical patterns in asset returns that cannot be explained by standard asset pricing models. Examples of well-known anomalies are value, momentum, size, low-risk and short-term reversal. Currently, there is no consensus in the academic literature on the underlying causes of these anomalies. The explanations that have been given in different studies can be grouped into four categories: 1) the anomaly is a result of data mining; 2) the anomaly disappears when trading costs are taken into account; 3) the return premium associated with the anomaly is a compensation for a particular form of risk or 4) the anomaly has a behavioral explanation, meaning that behavior of market participants systematically influences asset prices and thereby causes market inefficiencies. The motivation of this thesis is to gain more and better insight into possible explanations for well-known asset pricing anomalies. Each of the chapters of this thesis focuses on one of the four categories of explanations for asset pricing anomalies.

In the second chapter we analyze whether well-known asset pricing anomalies, such as value and momentum effects, are also present in the new emerging equity markets, the so-called frontier emerging markets. The focus in this chapter is on the data mining explanation, as we investigate whether asset pricing anomalies that have been documented in developed countries also exist in these markets, where they have not been analyzed before. We document the presence of economically and statistically significant value and momentum effects, and a local size effect and can therefore conclude that data mining as an explanation for these effects is unlikely. Our results indicate that the value and momentum effects still exist when incorporating conservative assumptions of transaction costs. Additionally, we show that value, momentum, and local size returns in frontier markets cannot be explained by global risk factors.

The third chapter focuses on trading costs as a possible explanation for the short-term reversal anomaly. Although trading costs are relevant for every asset pricing anomaly when it is being exploited by investors, the short-term reversal effect is the most interesting anomaly on which to analyze the effect. Gross returns are very high for this strategy, but so are turnover and therefore trading costs. The trade-off between gross returns and trading costs for this strategy is therefore extremely delicate. Several studies report that the return premium associated with short-term reversal investment strategies diminishes once trading costs are taken into account. We show that the impact of trading costs on the strategies' profitability can largely be attributed to excessive trading in small-cap stocks. Limiting the stock universe to large-cap stocks significantly reduces trading costs. Applying a more

sophisticated portfolio construction algorithm to lower turnover reduces trading costs even further. Our finding that reversal strategies generate 30–50 basis points per week net of trading costs poses a serious challenge to standard rational asset pricing models.

In the fourth chapter we examine risk as an explanation for the value and size effects. We revisit the question whether the Fama-French factors are a manifestation of distress risk premiums. To this end, we develop new tests specifically aimed at dissecting the Fama-French factor returns from a distress risk premium. While we find that value and small-cap exposures are typically associated with distress risk, our results also indicate that distress risk is not priced and that the small-cap and value premiums are priced beyond distress risk. Moreover, the distress risk exposures of common small-cap and value factors do not have explanatory power in asset pricing tests. Our results have important implications for investors engaging in small-cap and value strategies, as by avoiding distress risk, they can capture the value and small-cap premiums with much lower risk.

In the fifth and final chapter we examine a behavioral explanation for the low-risk anomaly. We investigate the relation between tournament behavior of mutual fund managers and the low-risk anomaly. Based on a general equilibrium model we show that tournament behavior causes the returns of low-risk (high-risk) assets to be larger (smaller) than expected according to the Capital Asset Pricing Model. Using mutual fund data and pricing data of individual assets from twelve different asset categories, we find a positive and significant relation between tournament behavior and the low-risk premium. The results indicate that the low-risk effect is not only more prominent in a period following stronger tournament behavior, but this anomaly is also larger in asset categories where more tournament behavior is observed. As there is no reason to assume that tournament behavior among mutual fund managers is likely to disappear anytime soon, investors can be more confident to capture the low-risk premium going forward.

Samenvatting (summary in Dutch)

Dit proefschrift bespreekt mogelijke verklaringen voor anomalieën in de financiële markten: empirische patronen in rendementen van beleggingsobjecten die niet verklaard kunnen worden door standaard beleggingsmodellen. Voorbeelden van bekende anomalieën zijn waarde, momentum, *size*, laag-risico en kortetermijn-*reversal*. Momenteel is er geen consensus in de academische literatuur over de onderliggende oorzaken van deze anomalieën. De verklaringen die gegeven zijn in verschillende studies kunnen gegroepeerd worden in vier categorieën: 1) de anomalie is het resultaat van *data mining*; 2) de anomalie verdwijnt wanneer transactiekosten worden meegenomen; 3) de rendementspremie van de anomalie is een compensatie voor een bepaalde vorm van risico of 4) de anomalie heeft een gedragsverklaring, wat betekent dat het gedrag van marktdeelnemers de prijzen van beleggingsobjecten systematisch beïnvloedt en daardoor marktinefficiënties veroorzaakt. De motivatie voor dit proefschrift is om meer en beter inzicht te krijgen in de verschillende mogelijke verklaringen voor bekende anomalieën. Elke van de hoofdstukken richt zich op één van de vier categorieën van verklaringen voor deze anomalieën.

In het tweede hoofdstuk analyseren we of bekende anomalieën, zoals waarde- en momentumeffecten ook aanwezig zijn in de nieuwe opkomende markten, de zogenaamde frontier-markten. Dit hoofdstuk richt zich op de data mining-verklaring, aangezien we onderzoeken of bekende anomalieën die zijn gedocumenteerd in ontwikkelde markten, ook in deze markten bestaan, waar ze nog niet eerder zijn onderzocht. We documenteren de aanwezigheid van economisch en statistisch significante waarde- en momentumeffecten, en een lokaal size-effect en concluderen daarom dat data mining een onwaarschijnlijke verklaring is voor deze effecten. Onze resultaten wijzen erop dat de waarde- en momentumeffecten nog steeds bestaan wanneer we conservatieve aannames gebruiken of transactiekosten meenemen. Bovendien laten we zien dat waarde-, momentum- en lokale size-rendementen in frontier-markten niet kunnen worden verklaard door wereldwijde risicofactoren.

In het derde hoofdstuk staan transactiekosten als een mogelijke verklaring voor de kortetermijn-reversal-anomalie centraal. Al zijn transactiekosten relevant voor elke financiële anomalie wanneer beleggers deze willen exploiteren, het kortetermijn-reversal-effect is de meest interessante anomalie om dit effect te analyseren. Brutorendementen zijn namelijk erg hoog voor deze strategie, maar ook de omzet en daarmee de transactiekosten. Het is daarom belangrijk een zorgvuldige afweging te maken tussen brutorendementen en transactiekosten. Verschillende studies rapporteren dat de rendementspremie die samenhangt met kortetermijn-reversal-beleggingsstrategieën verdwijnt zodra rekening

wordt gehouden met transactiekosten. We tonen aan dat de impact van de transactiekosten op de winstgevendheid van de strategieën grotendeels kan worden toegeschreven aan overmatige handel in kleine aandelen, d.w.z. aandelen met een lage marktwaarde. Het beperken van het aandelenuniversum tot grote aandelen, d.w.z. aandelen met een hoge marktwaarde, verlaagt de transactiekosten aanzienlijk. Het toepassen van een meer geavanceerd portefeuilleconstructiealgoritme om de omzet te reduceren verlaagt transactiekosten nog verder. Onze bevinding dat reversal-strategieën 30 tot 50 basispunten per week genereren na aftrek van transactiekosten, vormt een serieuze uitdaging voor veel gebruikte beleggingsmodellen.

In het vierde hoofdstuk analyseren we risico als een verklaring voor het waarde- en het size-effect. We heronderzoeken de vraag of de Fama-French-factoren een manifestatie zijn van de faillissementspremie. Hiervoor ontwikkelen we nieuwe testen die specifiek gericht zijn op de opsplitsing van de Fama-French-factorrendementen van een faillissementspremie. Ondanks dat we vinden dat waardeaandelen en aandelen met een lage marktwaarde vaak samenhangen met een hoger faillissementsrisico, geven onze resultaten ook aan dat faillissementsrisico niet geprijsd is en dat de premies op waardeaandelen en kleine aandelen buiten faillissementsrisico zijn geprijsd. Bovendien, het faillissementsrisico behorend bij typische size- en waardefactoren heeft geen verklarende kracht in asset pricing-testen. Onze resultaten hebben belangrijke gevolgen voor beleggers die beleggen volgens size- en waardestrategieën, omdat door het vermijden van faillissementsrisico beleggers beter in staat zijn om waarde- en small-cap-premies te verdienen met veel lager risico.

In het vijfde en laatste hoofdstuk onderzoeken we een gedragsverklaring voor de laag-risico anomalie. We onderzoeken de relatie tussen toernooigedrag van managers van beleggingsfondsen en de laag-risicoanomalie. Op basis van een algemeen evenwichtsmodel laten we zien dat toernooigedrag ervoor zorgt dat de rendementen van laag-risico (risicovolle) beleggingsobjecten groter (kleiner) zijn dan verwacht volgens het Capital Asset Pricing Model. Met behulp van data van beleggingsfondsen en prijsdata van afzonderlijke beleggingsobjecten uit twaalf verschillende beleggingscategorieën, vinden we een positieve en significante relatie tussen toernooigedrag en de laag-risico premie. De resultaten wijzen erop dat het laag-risico-effect niet alleen prominenter aanwezig is in een periode volgend op sterker toernooigedrag, maar ook sterker is in beleggingscategorieën waar meer toernooigedrag is waargenomen. Omdat er geen reden is om aan te nemen dat toernooigedrag tussen managers van fondsen verdwijnt, kunnen beleggers meer vertrouwen hebben om in de toekomst de premie op laag-risicoaandelen te verdienen.

About the author

Wilma de Groot (1979) studied Econometrics and Operations Research at Tilburg university from 1997 to 2001. After receiving her Master degree in 2001 she joined Robeco as a Quantitative Researcher, focusing on equity research. Soon afterwards, Robeco introduced its first purely quantitative equity strategy for which Wilma developed the portfolio construction software. Fifteen years later, this business had grown to around 40 billion euros assets under management. As a spin-off of her research Wilma has published papers in the Journal of Banking and Finance, Journal of Empirical Finance, Financial Analysts Journal, Journal of Alternative Investments, Pensions and the VBA Journaal. Her studies have been presented at several international conferences and she has regularly given lectures at several universities. In 2008 she finished the education for Charted Financial Analyst at the CFA institute and is a CFA charter holder. Since 2014 Wilma is a Portfolio Manager within the Core Quant Equities team of Robeco.

Wilma's research interests include factor investing strategies. Besides her experience on this topic applied to equities she also has several publications in the field of commodity research. In addition, she has a broad interest in pension fund cases, which she experiences as board member of the Robeco Pension Fund (since 2013) and member of the Investment Committee.

Portfolio

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One of the most important challenges in the field of asset pricing is to understand anomalies: empirical patterns in asset returns that cannot be explained by standard asset pricing models. Currently, there is no consensus in the academic literature on the underlying causes of well-known anomalies, such as the value and momentum anomalies. Anomalies could be the result of data mining, disappear when trading costs are taken into account, be a compensation for a particular form of risk, or have a behavioral explanation. The motivation of this research project is to gain more and better insight into possible explanations for well-known asset pricing anomalies. Understanding asset pricing anomalies is of the utmost importance for investors. It allows them to make better informed investment decisions, and thereby achieve higher return premiums.

The first study in this dissertation shows that the value, momentum and size anomalies are also present in the new emerging equity markets, the so-called frontier emerging markets, which makes data mining as an explanation for these anomalies unlikely. The second study focuses on trading costs as a possible explanation for the short-term reversal anomaly. Focusing on large-cap stocks and applying a more sophisticated portfolio construction algorithm lower trading costs significantly, such that reversal strategies generate profitable results net of trading costs. The third study examines risk as an explanation for the value and size anomalies. Although value and small-cap exposures are typically associated with distress risk, the results indicate that distress risk is not priced and that the small-cap and value premiums are priced beyond distress risk. The fourth and last study examines a behavioral explanation for the low-risk anomaly. Based on a general equilibrium model, tournament behavior causes the returns of low-risk (high-risk) assets to be larger (smaller) than expected according to the Capital Asset Pricing Model. In addition, empirical analyses confirm a positive and significant relation between tournament behavior and the low-risk premium.

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