# Size and dividend yield effects in Europe

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**Abstract**

Applying a carefully screened European dataset, this thesis documents a “reversed” size effect for the period March 1999 to February 2017. The excess-or risk adjusted returns are analyzed in a univariate-as well as multivariate regression with variables size and dividend yield. Controlling for the January effect, the “reversed” size premium disappears. Excess return and dividend yield are negatively related. Once dividend yield is added as a control variable in a multivariate regression of size and excess return the “reversed” size premium lives on. This thesis adds to current literature in the sense that recent empirical tests of the size effect in Europe are short in supply. In addition, according to my knowledge no paper has analyzed the relation of size and dividend yield in Europe whilst taking into account individual firm observations in the Fama-MacBeth regressions.

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# 1. Introduction

## 1.1 General introduction

When it comes to overall reputation, large cap stocks are superior to small cap stocks. The small firms are received as high-risk companies, due to their instability and likelihood of bankruptcy. From the 1980's however, a turning point with regard to investing arises. Academics as well as financial practitioners observe an interesting pattern in return analysis of small firms compared to large companies. Namely, the returns of smaller stocks seem to outperform that of their larger peers, on average. Small firm investment funds were created and aimed to exploit this so called "size effect". Although evidence in favor of the size effect started from the eighties, consensus about its existence is still lacking.

In 1981 Banz was the first who investigated the empirical relationship between return and size, by analyzing market value of NYSE common stocks for the period 1936-1975. In the sample Banz (1981) found that smaller firms earned higher risk-adjusted returns compared to larger firms, on average. The "size" effect is not linear to market value in the sample. Banz (1981) cautions to make statements whether "size" is responsible for the phenomenon, it could be that size is just a proxy for unknown variables correlated to size. After Banz (1981) several other academic papers investigated the size effect. Van Dijk (2011) reviews influential academic papers related to the size effect from the three passed decennia in the U.S. Despite different sample selection criteria and portfolio sorting techniques most of them found higher returns for smaller firms than for larger firms, on average.

Peek (2015) extends the size effect analysis to the European Market. On one hand as a robustness check to U.S findings, on the other hand providing analysts a guideline in assessing the small cap premium in a cost of equity computation for European stocks. Peek (2015) argues that earlier academic papers related to non-U. S size premium effects suffer from small sample size problems, especially when focused on one particular country. This research investigates a potential small firm premium in a dataset hypothesized to mimic Europe. As van Dijk (2011) argues, is size effect research outside U.S samples quite sparse. Peek (2015) fills this gap with a large sample investigating a timeframe when European stock indices became increasingly integrated. Peek (2015) clears the path with his argument that due to globalization a multi-stock indices analysis is possible. This research uses the argument of integrated markets as a way to analyze the size effect in Europe.

Another question which caught the attention of researchers, is whether size is merely a proxy for some unknown risk factor correlated to size (Banz, 1981). For example, liquidity risk, momentum and infrequent trading risk (de Moor & Sercu, 2013). Above mentioned explanations for the size premium are intensely investigated. Underexposed in current literature is the ability of dividend yields to be the missing risk factor. De Moor & Sercu (2013) find results in their global sample that advocate dividend yields to play an important role in the missing risk factor. Inspired by de Moor & Sercu (2013), this thesis investigates the explanatory power of dividend yields with regard to size effects in Europe.

### 1.2 Issue in perspective

The size effect or size "anomaly" is an intensely debated topic in financial economics. Nevertheless, there are several concerns with regard to current literature. As van Dijk (2011) argues, most of the papers on the size effect are outdated and the empirical methods vary to such a degree that it is very hard to compare results. The second issue is related to sample selection. The majority of the papers are solely focused on U.S markets, which makes it hard judge whether size effects occur or that it is just a region-specific event. Lastly, as mentioned in the introduction it is still not known what the driving factor is behind size effects. Whether the abnormal returns are due to size itself or some unknown risk factor correlated to size is unclear (Fama and French, 1992).

The size premium conquered a serious although ambiguous position in asset pricing tests since it's discovery in the eighties. Firm characteristics as financial distress risk, liquidity risk and exchange risk are often hypothesized to explain size effects in academic papers (Amihud, 2002). Financial practitioners often apply a small firm premium whilst computing the cost of equity for companies. Evolution of the size effect over recent years can have implications for usage of the small firm premium in valuation analysis.

This thesis adds to existing literature in the sense that size premium tests focused on the European market are short in supply. In addition, according to my knowledge no paper has analyzed the relation of dividend yield to size effects in a European dataset whilst taking into account individual firms in the Fama-MacBeth regressions.

### 1.3 Research design

This thesis aims to answer several hypotheses with regard to the size effect. Especially, this thesis is designed to scrutinize on size effect aspects which deserve more attention compared to their current status in existing literature, theoretically as well as empirically. De Moor & Sercu (2013) mention in their global size premium research that the dividend yields as a risk-factor are too interesting to ignore, whilst being little exposed in existing studies. For that reason, to fill the gap with existing literature, the research question exists of two building blocks 1) The influence of firm size on European stock returns 2) How the dividend yield hypothesis is related to this possible influence. The main research question that combines these building blocks is shown below:

"***To what extent are dividend yields able to explain the relationship between firm size and excess returns for firms listed on the European Market?"***

In the literature review past and recent studies with regard to CAPM, the dividend yields and other aspects of size premium research are discussed. The CAPM deserves attention in the literature review because to understand and interpret size effect tests, which are conducted in the regression part, one needs to have knowledge about size premium measurement vehicles. CAPM is such a vehicle. So, advanced asset pricing modeling knowledge is a pre-to conduct size premium tests. The following questions are discussed in the literature review, with the aim of better understanding asset pricing as well as size premium tests:

1) ***"What are the underlying thoughts of securities' pricing and why?"***

2) ***"Do small firms earn excess returns over large firms? If this this holds, what phenomena could explain this so-called size premium? "***

3) ***"If firms apply different dividend payout ratios, how could this influence the cross-section of returns in Europe?"***

## 2. Literature review

### 2.1 The Capital Asset Pricing Model

This section is dedicated to the development of CAPM. CAPM is one of the most discussed topics in corporate finance. The focus is on CAPM developments which are of interest to the research.

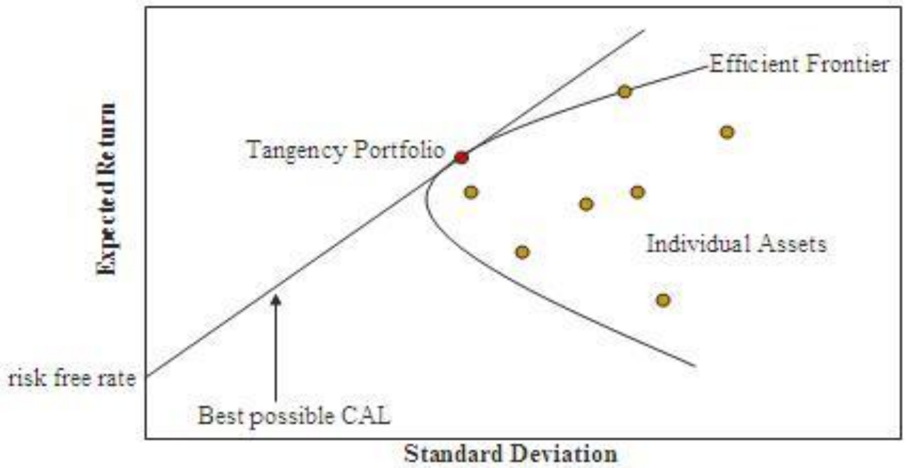
#### 2.1.1 Origination Process

The capital asset pricing model was founded in 1964 by William Sharpe. Lintner (1965) and Black (1972) contributed to the development of CAPM foundations which are today known as the "traditional" CAPM. In general asset pricing models aim to predict the risk-return relationship of securities as close to real as possible. Once these relations are mapped correctly portfolios can be compiled according to risk-return preferences of an investor.

The portfolio selection theory by Markowitz (1952,1959) gave inspiration to asset pricing modeling. Pillars of Markowitz (1952,1959) work, as is for asset pricing, is the relation between return, risk, asset correlation and portfolio diversification. Markowitz (1952,1959) main finding is that once two risky assets are combined, the standard deviation of these assets compiled is less than the sum of the individual asset standard deviations. For a large portfolio of stocks this definition implicates that an asset's risk and return should not be assessed by its own, rather how to the asset contributes to the overall risk and return of a portfolio. The Markowitz (1952,1959) portfolio selection theory is the essence of above statements. The theory provides investors guidance in constructing the optimal individual portfolio by carefully assembling assets. Off course several simplified assumptions must be made with regard to investor preferences and market conditions once applying the Markowitz (1952,1959) portfolio selection theory, which is also known as the birth of Modern Portfolio Theory(MPT). Due to these simplified assumptions, practical implementation of MPT occurred rarely (Elton et al. ,1976).

Before Sharpe (1964) extended MPT to a testable model, Tobin (1958) added valuable insights. Tobin (1958) strikes Markowitz that he only takes into account risky assets, whilst constructing the optimal portfolio. Tobin (1958) brings in leverage. In this case leverage is referred to risk-free borrowing and lending. Optimal portfolio construction now essentially exists out of two building blocks; 1) Optimal selection of risky assets 2) Optimal relation of risky assets to a risk-free investment. This process is known as Tobin's separation theorem. The main contributions of Markowitz (1952,1959) and Tobin (1958) are graphically depicted in figure 1.

Figure 1) Source: Wikipedia




The aforementioned building block 1) Optimal selection of risky assets, is visible in the upper-half of the hyperbola. This line represents all portfolio combinations which are “mean-variance” efficient. According to Markowitz investors only care about the mean and variance of their one period portfolio returns, which implicates that investors will choose a mean-efficient portfolio on the upper-half of the hyperbola. For this reason, the Markowitz model is often referred to as being the “mean-efficient” model (Fama and French, 2004). Risk in this case is measured in standard deviation, the square root of the variance. MPT baptized this upper-half of the hyperbola to the “mean-efficient frontier”, simplified “efficient-frontier. Building block 2) of portfolio selection, introduced by Tobin (1958), is shown as the Capital Allocation Line(CAL) in figure 1. Key addition to the Markowitz efficient frontier is bringing in leverage. Once investors are able to borrow and lend at the risk- free rate, the risk-return relationship of a risky asset(portfolio) combined with the risk-free asset becomes linear. One can vary between proportions invested in the risk-free asset and the risky portfolio, this variation will lead to up-or-down movement on the CAL, according to risk-return preferences of an investor. Introducing the risk-free asset causes the CAL to be the new efficient-frontier. The tangency portfolio in figure 1 represents a 100% investment in the risky asset, with the highest possible Sharpe ratio. The Sharpe ratio is a performance measure to adjust an investment for its risk. So, the highest possible Sharpe ratio means the optimum risk-return relation.  The Sharpe ratio is the variable in the CAL equation.  The formula of the CAL is visible below.

$$(2)\ CAL\ E(Rc) = Rf + \sigma c \frac{E(Rp) - Rp}{\sigma p}$$

In this formula C is a combination portfolio of investments in a risky asset portfolio P and a risk-free asset F. The efficient frontier with only risky assets by Markowitz (1952,1959) is able to produce only one point, the Tangency Portfolio, which offers the highest Sharpe Ratio. Tobin’s (1958) introduction of the risk-free asset causes the CAL to produce “combination” portfolios which are able to produce Tangency Portfolios at different risk-return levels. Expanding investors choices. All portfolios on the CAL are superior to the upper-half hyperbole efficient frontier of Markowitz (1952,1959), except the Tangency Portfolio point in figure 1. As mentioned earlier the portfolios on the efficient frontier are theoretically compiled of all risky assets in the market. One can imagine that in practice it is impossible to determine the tangency portfolio taking into account all risky assets variances and covariance's. Sharpe (1964) came up with a possible solution, which will be elaborated in the next section.

### 2.1.2 Establishment of Traditional CAPM

#### 2.1.2.1 Sharpe-Lintner

The single factor CAPM extends the findings of Markowitz (1952,1959) and Tobin (1958) into a testable application. As mentioned earlier several simplified assumptions are necessary for MPT. Sharpe (1964) and Lintner (1965) add two key assumptions used for identifying a mean-variance efficient portfolio, which led to establishment of CAPM. *Complete agreement* and *borrowing and lending at a risk-free rate* (Fama and French, 2004).

*Complete agreement* is related to investor uniformness in the distribution of returns. At t-1 the market decides the clearing asset prices of all available assets, and investors agree on the combined asset return distribution from t-1 to t. Implying that there is only one "true" return distribution. The returns of this joint "true" distribution are inputs of CAPM tests. Following Tobin's separation theorem, Sharpe (1964) and Lintner (1965) add *borrowing and lending at a risk-free rate* as a formal assumption to the one-factor model. This risk-free rate is the same to all investors and has no relation to the amount borrowed or lend, implying it is constant. Once investors agree completely about one "joint" return distribution, they also observe the same set of investment opportunities. Assuming only risky-assets, the investors uniform view causes all investors to choose the tangency portfolio on the Markowitz efficient frontier (see figure 1). Because all investors choose the tangency portfolio it must be the value-weighted market portfolio. Adding the risk-free rate causes investors to combine the tangency portfolio with a preferred amount of borrowing or lending.

So far, the additions of Sharpe (1964) and Linter (1965) do not appear to be very different from what Tobin and Markowitz already discovered. One must interpret above statements carefully to assess the contribution of Sharpe (1964) and Lintner (1965). Essential for CAPM are the *complete agreement* and *risk-free borrowing and lending* assumptions, which imply that the market portfolio M is on the mean-variance efficient frontier, if the market is to clear asset prices (Fama and French, 2004). Following above, all minimum-variance efficient portfolios must be constructed with regard to the value-weighted market portfolio M. The formula for the condition is visible below:

$$(3)\ Minimum\ Variance\ Condition\ E(Ri) = E(Rzm) +\ \beta im\big(E(rm) - E(Rzm)\big)$$
$$For\ i = 1, \ldots., N\ Risky\ Assets$$

$E(Ri)$ is the return on asset *I*, a portfolio or an individual asset. $E(Rzm)$ is the return on an asset which is uncorrelated to the market return, implying a beta of zero $\beta im$, the market beta of asset *I*, measures the sensitivity of asset *i* returns to the excess market return. It is computed as the covariance of the asset *I* return divided by the variance of the market return (Fama and French, 2004).

$$(4)\ Market\ Beta\ \ \beta im = \frac{cov(Ri, Rm)}{\sigma^2(Rm)}$$

Formula 3 & 4 already appears to economy students as being foundations of CAPM. The SL-model(Sharpe-Lintner) adds *risk-free borrowing and lending* to formula (3) to identify $E(Rzm)$. Once *risk-free borrowing and lending* is applied, the expected return of assets that are uncorrelated to the expected market return, must converge to the constant risk-free rate $Rf$. The identification of $E(Rzm)$ as $Rf$, due to *risk-free borrowing and lending*, leads to the familiar Sharpe-Lintner CAPM formula (Fama and French, 2004).

$$(5)\ Sharpe - Lintner\ CAPM\ E(Ri) = Rf + \ \ \beta im\big(E(Rm) - E(Rf)\big)$$
$$For\ i = 1, \ldots., N\ Risky\ Assets$$

In words, condition (5) describes the relationship between expected return of an asset/portfolio of assets and systematic or market risk. Because the market portfolio is efficient, all securities' individual risk can be diversified away. A securities *sensitivity* to the market risk is what stays behind, which is proxied by the securities market beta $\beta im$ times the market risk premium $\beta im\big(E(Rm) - E(Rf)\big)$ . In addition, a compensation for the *time value* of money comes in the form of the return on the risk-free asset $Rf$.

#### 2.1.2.2 Black

After introduction of the Sharpe-Lintner model several researchers restated the model, as scientists today still do. Due to its strong and often unrealistic assumptions an ongoing debate goes whether CAPM, and in which form, is a solid asset pricing tool.

The first scientist which restatement had significant impact was Fischer Black in 1972. He argued that the unrealistic assumption *risk-free borrowing and lending* can be replaced by another unrealistic assumption; *unrestricted short sales of risky assets* (Fama and French,2004).

What does this assumption substitution in the ending contributed to CAPM? Only the interpretation of the variable $E(Rzm)$ in the minimum variance condition (3) changes. The Black variant argues that $E(Rzm)$ must be less than the expected market return, implying that the market risk premium is positive (Fama and French,2004). As aforementioned the Sharpe-Lintner assumption of *risk-free borrowing and lending* leads $E(Rzm)$ to be the risk-free rate. Both unrealistic assumptions are applied with the same goal, to assure efficiency of the market portfolio in algebraic terms. When there is no complete *risk-free borrowing and lending* nor *short selling*, investors still choose portfolios on the mean-variance frontier in figure 1. But the algebra behind portfolio efficiency, in the absence of above unrealistic assumptions, argues that a portfolio made up of efficient portfolios isn't necessarily efficient (Fama and French, 2004). One can expect what this means to the market portfolio, which is a value-weighted portfolio of all efficient portfolios. Efficiency can't be guaranteed, losing CAPM" s relation between expected return and market beta.

### 2.1.3 Justification

Economists agree that many of CAPM assumptions are impossible to implement in reality. It is highly unlikely that all investors have the same expectations regarding future returns and their accompanying risk. Or assuming that markets are perfectly competitive and investors can borrow and lend at the same risk-free rate. Although theoretic assumptions are heavily debated in academic literature, the hart of the issue is from an empirical perspective. Several researchers have showed that easing assumptions does not necessarily violate CAPM. In the preceding sections, it is described that Black (1972) shows that losing the assumption of risk-free borrowing and lending does not bring the CAPM relation in danger. Lintner (1965) as well describes a variant of CAPM without the assumption of complete agreement and it seems to be similar in explaining risk and return.

Early empirical tests of CAPM have a tendency to reject the Sharpe-Lintner (1965) variant. Following Fama and French (2004) three predictions about CAPM are taken into account in empirical tests. There is a linear relation between excess market returns and expected asset returns in the form of beta. The market factor is the only explanatory variable. Assets uncorrelated to the market have a return equal to the risk-free rate. To test the predictions cross-sectional as well as time-series regressions are applied.

The early cross-sectional tests made clear that there were estimation problems. At first, betas measured for single firms appeared to suffer from impreciseness. When these individual beta estimates are used in explaining average returns measurement errors are created. Another issue is related to the correlation of residuals in regressions. When residuals are indeed correlated, which can be due to for instance industry effects, the standard error in the regression is biased downwards.

Researchers propose solutions to the estimation problems. They confirmed that CAPM prediction tests can be applied to portfolios of assets instead of single assets, and the estimations of portfolio betas are more precise. The influential papers starting with Blume (1970) adopted to portfolio estimation of beta. Fama and Macbeth (1973) compose a study framework with the aim of limiting the correlation of residuals. They achieve this by forming a two-pass regression. At first a time-series regression is applied to measure time-series averages for beta and the intercept. The betas from step 1 are used in a month-by-month cross-sectional regression instead of a single cross-section. Due to the repeated sampling of a multiple period cross-section the correlation in residuals is resolved. The introduction of a time-series CAPM regression in 1968 by Jensen thus appeared to be vital in resolving estimation problems. He formulated the relation of expected return and market risk over time as follows:

$$(6)\ R_{it} - R_{ft} = \alpha_i + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \ \varepsilon_i$$

Traditional CAPM requires an $\alpha_i$ of zero, otherwise other factors besides market risk influence expected returns. In addition, it requires that the assets or portfolios return is completely explained by the CAPM risk premium. All influential papers after Jensen (1968) testing CAPM as Blume (1970) and Miller and Scholes (1972) are having a hard time confirming the coefficient on beta equals the market return in excess of the risk-free rate, they report lower coefficients. Implicating that the relation between beta and average return is too flat (Fama and French, 2004).

They all report alphas in excess of the risk-free rate. In essence meaning that a sole market risk factor is insufficient in explaining asset returns.

Logically academics question thereafter whether other factors are able to explain the variation in average returns, due to the lacking power of a single market factor. As aforementioned Banz (1981) found that on a risk-adjusted basis, small firms produce higher returns over larger firms. Risk-adjusted in the sense that there is controlled for CAPM predicted returns. Whether size or another factor is responsible is unknown. Because CAPM is unable to explain the return variation, as is the case with Banz (1981), one refers to a CAPM anomaly.

After Banz (1981) more researchers found evidence in favor of misspecification of traditional CAPM. Numerous factors are supported by empirical evidence to be a valid addition to traditional CAPM. In 1992 Fama and French review the factors presumed to be of relevance in relation to average returns. They argue that size-and value mimicking portfolios suffices in explaining average returns. These mimicking portfolios seem to capture the leverage effect of Bhandari (1988) and the E/P ratio of Basu (1983) on average returns as well. Most strikingly Fama and French (1992) report that once controlled for size there is no relation between average returns and beta, in the sample of U.S stocks between 1963-1990. Fletcher (2000) as well as Pettengil et al. (1995) confirm this flat relation between beta and average return.

Abundance of research thus claim CAPM to be insufficient in explaining average returns. According to Roll (1977) it is in fact impossible to truly test CAPM due to the inability of measuring a market portfolio of all assets, and the use of proxies already creates error. Fama and French (2004) note that this holds for every model making use of proxies, once again critical judgement is necessary to argue whether theoretic models are applicable on real-life data. Because this research is focused on the relation of average returns to size and dividends, modifications of CAPM are not discussed in detail. The methodology that is superior with regard to this particular research is discussed in chapter 4. In the following section attention is geared towards size effects.

# 3. Size effect

This section focusses on the rise, the critique and possible explanations of the size effect. The widespread discussion in academic atmospheres makes the size affect possibly the most famous CAPM Anomaly, since Fama and French (2004) claimed it to be an anomaly. However, common sense about the size effect is still lacking.

## 3.1 Size effect evidence

### 3.1.1 United States

As mentioned in the introduction Banz (1981) was the first to find evidence for size effect patterns in U.S stocks returns. He investigates common stock returns listed on the NYSE, for the period 1936-1975. The common stocks are subdivided in quintile size portfolios; the smallest quintile produces risk-adjusted returns 0.40% higher than the remaining. Banz findings induce misspecification of CAPM, suggesting a size premium is present.

After Banz (1981) numerous scientist perform analysis on U.S stock returns. The decade following Banz (1981) primarily advocates his findings of an existing size premium. Thereafter, also contradicting arguments arrive. This section refers to “size premium” as being the monthly return differential between the smallest and largest portfolio. Studies in this section also differ in the number of size portfolios applied in their analysis.

Reinganum (1981) investigates the size effect in a dataset consisting of 566 NYSE and Amex stocks over the period 1963-1977. In this partly Banz (1981) overlapping dataset he finds the smallest decile to outperform the largest by 1.77% monthly. Brown et al(1983b) perform an analysis on the sample set by Reinganum (1981). They find an approximately linear relation between the logarithm of the average market cap and the average daily return on size decile portfolios. Keim (1983) adds two more years of observation to the Amex/NYSE analysis, resulting in a 1963-1979 timeframe. His size decile portfolio research reports a size premium of 2.52 percent. In addition, he finds the premium to be partly explained by the beta differences of large versus small stocks. Nevertheless, these differences are not able to fully guarantee for the observed size premium. Lamoureux and Sanger (1989) extend the scope by analyzing NYSE/Amex as well as Nasdaq firms over the period 1973-1985. They investigate Nasdaq and NYSE/Amex separately. But in both samples, form 20 portfolios based on size and examine the return differentials. Taking into account Nasdaq stocks, they even report lower beta for small firms versus large firms, contradicting earlier findings.

One must be very careful when comparing above studies, even interpreting the study results individually. Except Banz (1981), all above studies measure returns on univariate size-sorted portfolios unadjusted for risk. In addition, they compute returns differently. Some studies examine returns in excess of the risk-free rate, others in excess of the market return.

Studies after Banz (1981) in the eighties have numerous contributions, but with Fama and French (1992) their innovative approach a call for paradigm substitution with regard to traditional CAPM is a fact. Fama and French (1992) add two factors to CAPM, size and book-to-market. Their sample consists of NYSE, Amex and Nasdaq stocks in the period 1963-1990. They find a return differential between the smallest and largest size decile of 0.63% monthly. Once each size decile is subdivided in 10 beta-size sorted portfolios, they find no relation between beta and returns. Besides introduction of two additional factors, the multivariate size-beta sorting technique differs from earlier univariate size sorting. Fama-MacBeth regressions support the lacking explanatory power of beta on returns, whilst size and book-to-market factors appear to have significant explanatory power.

### 3.1.2 International

Although early studies are focused on U.S markets, from the late eighties researchers expand their horizon into an international environment. Global as well as country or region-specific studies gain a foothold in academic literature. For several reasons, these studies are important to this particular thesis as well as completeness of size premium tests. Countries differ in economic environments, for investors and economic policymakers it is important to know if and how size premiums exist and evolve within clearly defined markets. These markets differ amongst other in trading mechanism, type of investors and market efficiency (Van Dijk, 2011). In addition, Lo and

MacKinlay (1990) and Black (1993) warn for data mining concerns related to U.S evidence. Expanding studies to other markets as well as time periods, provides a voice against these concerns.

Remarkable is that most of these international studies show a stable pattern in favor of size premiums. Van Dijk (2011) evaluates 19 non-U. S studies. Because this thesis focusses on the European market, attention is geared towards European studies with respect to the international section. The monthly size premiums for individual European countries evaluated by van Dijk (2011), ranges from 0.13% in the Netherlands (Doeswijk,1997) to 1.18% in the UK (Bagella et al., 2000). In a Pan-European study by Annaert et al. (2002) for the period 1974-2000 the monthly size premium counts 1.45% monthly. Probably driven by countries not evaluated separately. Only the result of the Dutch size premium by Doeswijk (1997) for the period 1973-1995 is insignificant, compared to significant results for countries as Spain, Germany and French. Despite the fact that these studies suggest that data mining concerns are minimal, and that U. S size premium tests seem to be robust to other markets, there are implications.

Many studies do not attempt to control for risk in returns at all, which makes it difficult to judge if size actually drives the premiums. The sample composition is often questionable. Studies that investigate 10 years or less, fewer than 100 stocks, or sort size in less than 5 portfolios are unlikely to find reliable results for the size premium (de Moor & Sercu, 2013). Lastly, it lacks agreement whether to measure size absolute or relative. If a firm's size is measured relative to the country average, a country which exists of manly small firms would have an upward bias in an international sample. The locally large but international small firms should move around the lowest size deciles in an international sample, due to the relative size value they move in higher size deciles. On the other hand, when measuring size absolute, it is hard to distinguish between country and size effects (Van Dijk, 2011). Heston et al. (1999) and Barry et al. (2002) argue that their empirical methods work best using relative size. Heston et al. (1999) find the size effect in their 12 European country sample to be almost fully driven by within-country size variation, advocating relative size. Barry et al. (2002) investigate 35 emerging markets, they only find evidence for size effects when size is measured relative to the country average. Rouwenhorst (1999) as well as Annaert et al. (2002) report it the other way around, size effect evidence only appears when size is measured absolute. Once again, there is no census related to an ideal size measure.

### 3.1.3 Size paradigm change

The nighties and early years after the turn of century are dominated by studies who claim the size premium has disappeared after 1980, or even changed in direction. Horowitz et al. (2000) apply three different methodologies to investigate a potential size effect in the timeframe 1980-1996. Applying annual compounded returns, monthly cross-sectional regressions and linear spline regressions they are unable to find evidence of a statistical size premium. In addition, Horowitz et al. (1999) as well as Dimson and Marsh (1999) even discovered arguments advocating a reversed size premium in the two decades after Banz (1981). Implicating that large firms tend to have higher returns than small firms. Interestingly, Dimshon and Marsh (1999) report an incredible reversal effect of the U.S size premium, between 1955 and 1988 the size premium averaged 5.9% per year, whilst in the period 1989-1997 this amount dropped to -5.6%. Size measurements are the same for both periods, implicating that measurement differences can't be of influence for the size premium.

Chen et al. (2000) mention that for the period 1984-1998 the Russel 1000 index of large cap stocks beats its metaphorical brother the Russel 2000 small cap stocks, 17.71 versus 11.22 average annual percent return. In addition, Elswarapu and Reinganum (1993) as well as Dichev (1998) and Amihud (2002) all find no size premium in samples between 1980 and 2000. All studies above centered their efforts on the United States, Barry et al. (2002) mentioned in the preceding section, investigate 35 emerging markets. In the period 1985-2000 they find non-U. S evidence for disappearance of the size premium, once measured absolute.

Schwert (2003) argues that the size premium vanished due to investors who seek to profit with strategies based on the presumed anomaly. Other academics as well as practitioners claim deficient measurement techniques to be responsible for the size premium found at first instance, arguing that size premiums are merely the result of certain empirical approaches. Lo and Mackinlay (1990) report that when data is sorted on a certain characteristic, for example firm size, testing the returns of these characteristic sampled portfolios could lead to misleading statistical inferences. Van Dijk (2011) elaborates on the issue. As Fama and French (1992) and other academics already mention, sorting stocks into portfolios reduces the measurement error and enhances power of asset pricing tests. But it has its downside with regard to statistical inferences. Following van Dijk (2011), sorting and assessing characteristic based portfolios, it is hard to judge whether the results are born due to a relationship between the tested characteristic and alpha or between the characteristic and the measurement error.

Not only sorting procedures and its implications are criticized, several academics claim mismeasurement of the market portfolio to be of influence in presumed anomalies as the size effect. Roll and Ross (1994) investigate the sensitivity of OLS estimates to a chosen proxy for the market portfolio, in a cross-sectional setting. The most sensational finding they report is that even market portfolio proxies close to the mean-variance efficient frontier are able to produce zero slopes. In addition, Black (1993) argues that if other market portfolios are used than the "true" market portfolio, which consist of all assets, betas are estimated with error. As aforementioned measuring the "true" market portfolio is impossible in practice. Betas are thus always estimated with error according to Black. One can imagine, assuming Blacks argument, that stocks with low betas could have higher betas, on average, when the "true" market portfolio is applied. With regard to the size premium, this finding contradicts that higher returns for small firms are a result of higher market risk for these small stocks.

Van Dijk (2011) criticizes substantial size premium studies to suffer from low robustness of results. The Sample and Data section of this thesis elaborates on the concerns by van Dijk (2011).

Academic papers question the use of static asset pricing tools. Almost all size premium tests in the eighties apply static models, for that reason some scientists are skeptical about the results of those tests. Jagannathan and Wang (1996) investigate in a sample of NYSE/Amex stocks between 1962 and 1990 whether a conditional CAPM, which is able to make expected returns conditional on available information to investors, can explain the cross-sectional variation in returns. They sort stocks into 100 size-beta portfolios. Interestingly, they report that the conditional CAPM is 30 times stronger in explaining the cross-sectional return distribution than its static peer. 30% for the conditional versus 1% for the static model. Several other studies show evidence as well in favor of conditional versions of CAPM. Lewellen and Nagel (2006) doubt the validity of the studies in favor of conditional variants. They report that conditional versions of CAPM require too large time-variances in betas and expected returns. This in fact, implies that conditional variants are no better in explaining expected returns nor anomalies.

Despite the critical tendency to size tests originated the early nighties, several recent studies show evidence of size effects. For example, de Moor & Sercu (2013) as mentioned in size evidence section. In the following section the possible explanations of the size effect in current literature are analyzed.

### 3.1.4 Potential drivers of the size effect

Researchers as well as practitioners are still heavily in discussion with regard to potential drivers of size effects, assuming that the empirical finding of the size effect has explanatory power. Visions vary widely. Predominant in this discussion is the risk-based view. The risk-based view embraces that size proxies for risks that are not measured correctly or even neglected. This in fact, suggests that asset pricing models as CAPM fall in short.

As aforementioned Fama and French (1993) add two two risk factors to CAPM, related to size and book-to-market value. They construct portfolios mimicking these phenomena. For the U.S period 1963-1991 they argue that including their size and-value factors beats traditional CAPM easily. The empirical power of adding these two factors suggests evidence that they proxy for some unknown risk-factors that influence returns. Still, there is no clue which true risk-factors are proxied.

In a proceeding article Fama and French (1996) mention that financial distress potentially could be a presumed unknown risk-factor explaining size. Thereafter, several studies investigated the statement of Fama and French (1996) empirically. Vassalou and Xing (2004) report that the size effect only persists in the highest quintile of default risk sorted portfolios. Other studies measure financial distress differently, but find evidence as well that if one controls for financial distress, size effects seem to diminish or even disappear. Suggesting that financial distress is able to explain size effects.

Roll (1977) as well as others points to infrequent trading as a driver of size effects. Dimson (1979) argues that infrequent traded stocks tend to have a downward bias in their estimated betas, whilst the reverse holds for frequent traded stocks. Roll elaborates on Dimson (1979) that infrequent traded stocks in general are small firms and that large stocks often are the most frequent traded stocks. The biased divergence in beta estimation of large versus small stocks can be a driver of presumed size effects. Cohen et al. (1983) show how to control for non-synchronous trading between large versus small stocks.

Probably the most supported explanation for the size effect is related to liquidity and transaction costs. Empirical studies differ in measurement techniques, and so do their outcomes. Especially, researchers point out that liquidity is able to influence the cross-section in expected returns as a firm characteristic as well as a risk factor. More important to this research, illiquidity of small stocks tend to explain at least partly the small firm premium. Amihud (2002) chooses to approach liquidity as a risk-factor, for which stocks can be more or less sensitive. If then, smaller stocks are more sensitive to this risk-factor, the size effect can at least be partly explained by the liquidity risk-factor. He reports that smaller stocks are, on average, more sensitive to time-series variation in the price of market liquidity. Time-variations in the market price of liquidity thus influences the size premium for small stocks, although Amihud (2002) mentions that this influence is quite small. Acharcha and Pederson (2005) construct a model which relate expected returns to expected liquidity, using the liquidity proxy of Amihud (2002). In the cross-section of expected returns, they find that their model is able to produce higher explanatory power than traditional CAPM and that the illiquidity of small stocks partly explains the size premium.

Van Dijk (2011) mentions an alternative to risk-based explanations, namely from the side of investor behavior. Lakonishok et al. (1992) argue that in case of the value effect investors tend to overreact with regard to past performance. Value stocks often performed poor on the stock market lately, and when investors overestimate the negative effects from this into the future, the stock price of those value stocks will be too low. Which in turn, will be corrected with higher returns when the overreaction evaporates.  Similar way of thinking can be applied to size effects, although under-exposed in current literature.

Investors experience a differing amount of information between stocks. Information, as well as investor base, typically increase with firm size. As such, size effects could potentially be driven by information proxies as for example analyst coverage. According to Merton (1987) a stock with a small investor base and information about the stock is relatively rare, experiences higher expected returns. Advocating that information asymmetry is linked to size effects. In the following section the relation of stocks their dividend yield on expected returns is analyzed.

### 3.2 Dividend yield and expected returns

The beneficial tax treatment of capital gains compared to intertemporal payments to investors in the form of dividends, causes one traditionally to favor capital gains over dividends. Investors only accepted dividend payout policies by firms if they are compensated by higher expected returns, which has contributed to the tax-effect hypothesis that dividend yield is positively related to risk-adjusted expected returns (Brennan, 1970). Black and Scholes (1974) are not able to find any relationship between expected returns and dividend yield. They claim this to be caused by the phenomenon that if investors would demand higher returns for higher dividend yielding stocks, firms will lower their dividends and concede investors with capital gains. If investors choose dividends over capital gains, firms opt to reward investors with dividends. So, firms adjust to preferences of investors, which in turn is responsible for the non-existing relation between dividends and returns controlled for market beta risk. The phenomenon is called the dividend-neutrality hypothesis.

Blume (1970) is the first who explored a U-formed pattern between expected returns and dividend yields, when returns are adjusted for market beta risk. The excess returns of zero-dividend paying stocks is larger than medium-yield dividend paying stocks and high-yield stocks earn higher excess returns over small-to-medium dividend paying stocks. Keim (1985) confirms the U-shaped relation of Blume (1970). The remarkable high risk-adjusted returns of zero-dividend paying stocks in the research of Blume (1970) and Keim (1985) is according to Christie (1990) attributable to the performance of zero-yield penny stocks in the 1930s and does not hold in at least his sample. In a timeframe of 1945-1986 Christie (1990) investigates the performance of zero-yield dividend stocks compared to yielding stocks, for firms of similar size. Controlled for size Christie (1990) reports that stocks paying dividends outperform zero-yielding stocks significantly in terms of risk-adjusted returns. Which shows evidence in favor of a positive return-dividend relation advocating the tax-effect hypothesis of Brennan (1970). Christie (1970) however argues that the origination of the positive relation is not fully attributable to the tax treatment of dividends, rather investors how overvalue the future performance of non-dividend paying stocks. The research of Chen et al. (1990) shows that the relationship of dividends and expected returns is very sensitive to the risk factors applied, a familiar issue in financial economics. When market risk is the only risk factor, they indeed confirm a positive relation between expected return and dividend yield, cross-sectional as well as in a time-series regression. Once a second risk factor is added in the form of default risk any relationship between returns and dividends vanishes. For this research, the interplay between size and dividend is particularly of interest, which is elaborated in the next section.

### 3.2.1 Dividend yield and size

As above mentioned early research supports that the presumed positive relation between dividends and expected returns is due to the beneficial tax treatment of capital gains over dividends. Keim (1985) however, is interested if these tax effects are fully responsible or that anomalies as the size effect could have a role. He creates 5 size and 6 dividend yield portfolios, resulting in 30 categories. Evident is the concentration of the smallest firms on the NYSE in the zero and highest dividend yield portfolios, namely 57% of all of the smallest firms. The U-shaped relation of expected returns and dividends thus could be influenced by the size effect, higher returns for smaller stocks. Now that there is support for a relationship between size and dividends it is interesting to investigate whether a dividend variable could be linked to a missing variable in size premium tests.

Naranjo et al. (1998) investigate dividend yield effects measuring risk-adjusted returns with the Fama and French three-factor model, thus controlling for size in the form of the SMB variable. Once controlled for known anomalies the presumed positive relation between dividend yield and returns precedes, although not monotonic.

De Moor & Sercu (2013) explore whether dividend yields are able to explain excess returns of size portfolios, controlled for various phenomena as liquidity and financial distress risk. In the period between 1980-2009 they investigate a large international sample of 39 countries. When they sort portfolios on dividend yield they report a special variant of the U-shaped relation of average returns and dividend yields. Namely a peak of the zero dividend-yield portfolio with an average return of 1.35% per month, then a drop to 0.77% in the lowest dividend portfolio, from there a steadily growth to 1.85% average return for the highest decile portfolio. In addition, the size deciles suggest a negative relationship of size and dividend yields. The smallest size decile strikes an average dividend yield of 4.48%, moving steadily downwards to 2.90% for the largest size decile. These patterns rise the question whether dividends are able to explain size effects, at least partly. The risk-adjusted size portfolios are regressed on two dividend variables, the monthly dividend yield of the portfolio and the proportion of zero- dividend yield stocks in the portfolio. The dividend yield coefficient appears to have a significant effect in the cross-section of the risk-adjusted size portfolio returns in the international sample of de Moor & Sercu (2013).

# 4. Research design

The following part is dedicated to the hypotheses applied and their model specifications with the aim of answering the question whether size and dividend effects occur amongst European listed stocks, and if these effects occur what are the related risk premiums. In section 4.1 the constructed hypotheses are discussed, section 4.2 elaborates on the hypotheses in a methodological format. Lastly, the characteristics of the dataset are discussed.

## 4.1 Establishment of hypotheses

From the discussion of academic research in the literature review one can make up that the size effect is heavily investigated, although consensus about its existence and especially its drivers is far from unanimous. This research aims to examine the size effect in Europe and if dividend yields could be a missing risk-factor driving the size effect. The main research question with regard to the problem statement is:

"***To what extent are dividend yields able to explain the relationship between firm size and excess returns for firms listed on the European Market?"***

Research on the ability of dividend yields to be a missing risk factor in size premium tests is very limited. De Moor & Sercu (2013) inspired to conduct a research linking dividend yields to size effects. As aforementioned, they explore a dividend yield factor that captures a significant effect on risk-adjusted size portfolios. This thesis tests the robustness by analyzing a separate European instead of global sample. The size as well as dividend effects of de Moor & Sercu (2013) are more vulnerable to possible country specific effects, because the economic integration of all the 39 countries employed is highly questionable. Peek (2014) as well as other researchers claim the 15 countries in the sample of this research applied to be highly economically integrated, limiting possible country-specific effects.

In addition, whilst de Moor & Sercu (2013) as well as the majority of size effect literature takes into account portfolios when conducting statements, this thesis scopes to single firm observations. This guarantees that firm-specific information is kept in the FM-regressions (Fama and French,1992). The following hypotheses are made to support the final goal of answering the research question:

*1a)" Small firms earn on average higher excess returns over large firms listed on the European market"*

*1b)" Hypothesis 1a is robust to the January effect"*

*2) "Firms with higher dividend yield earn excess returns over firms with lower dividend yield"*

*3)" Once controlled for dividend yields, there are no excess returns with regard to size"*

#### 4.1.1 Hypothesis 1

*1a)" Small firms earn on average higher excess returns over large firms listed on the European market"*

*1b)" Hypothesis 1a is robust to the January effect"*

From the literature review, one can make up that hypothesis 1, which raises the question whether size effects occur, is heavily sensitive to measurement techniques. A much-supported critique is that risk-adjusted size portfolio returns in current research are not made subject to causality. Using the term risk-adjusted returns is highly ambiguous, due to the lacking definition of what is risk-adjusted. In most academic papers examining size effects risk-adjusted sums op to controlling for market beta risk measured with size portfolios, and once there is controlled for market beta risk excess returns of smaller firms over large firms advocates size effects. This thesis contributes to existing literature in the sense that once the market betas are measured with size portfolios and subsequently assigned to individual firms, these excess returns are regressed on a size variable. The relation between excess returns and the size variable is in fact an example of causality. The aim of hypothesis 1 is to see whether size and return have a relation in a cross-sectional setting applying the above explained variant of risk-adjusted.

In addition, several studies claim the size effect to be mostly driven by the January month. Van Dijk (2011) provides an overview of the seasonal patterns of stocks between 1927-2010 in the U.S and an extraordinary peak for January is visible. He argues that the effect is mostly due to the smallest size decile, and that the size effect in the U.S is driven by the January month. On the other hand, abundant research found size effects evidence controlled for January. Dimson et al. (2002) even did not find any evidence of seasonal behavior in stock returns. Hypothesis 1B is formulated with the expectation that size effects are not completely driven by the month January.

#### 4.1.2 Hypothesis 2

*2) "Firms with higher dividend yield earn excess returns over firms with lower dividend yield"*

Aforementioned is the discussion of the relation between risk-adjusted returns and dividend yields. Once again, ambiguity surrounds the definition of risk-adjusted. The general approach conducting statements about dividends and expected returns is analyzing portfolios sorted on dividend yields. Often there is a peak in risk-adjusted returns for the zero-dividend yield then a drop to the smallest dividend yield, from there a steady growth in excess returns to the highest dividend yield portfolio (De Moor & Sercu, 2013). The familiar V or U shape pattern described in the literature review. Except for the zero-yield portfolio effects above arguments are in favor of hypothesis 2, which provides the basis for formulating hypothesis 2. This research aims to improve the definition of risk-adjusted whilst analyzing the relation between risk-adjusted returns and dividend yields. In the model specification, there will be elaborated on the techniques used to define risk-adjusted.

#### 4.1.3 Hypothesis 3

*” Once controlled for dividend yields, there are no excess returns with regard to size”*

Based on current academic research one expects this hypothesis to be rejected. Naranjo et al. (1998) investigate dividend yield effects measuring risk-adjusted returns with the Fama and French three-factor model, thus controlling for size in the form of the SMB variable. Once controlled for known anomalies the presumed positive relation between dividend yield and returns proceeds, although not monotonic. The methodology of the Moor & Sercu (2013) is closer aligned to this thesis, their regression results suggest that dividend yields are indeed able to explain size effects, but not all of it. Hypothesis 3 is formulated to test whether dividend yields are able to explain size effects in the European sample.

### 4.2 Methodology

Now attention is geared towards modifying the hypotheses into testable applications. The following section describes the methods used and their theoretical support.

#### 4.2.1 Risk Premiums

Fama-MacBeth constructed in 1973 a methodological format for testing CAPM, since then it has become the standard in asset pricing tests. The aim of the model is to determine the sensitivity of asset or portfolio returns to one or more variables of interest. How the asset or portfolio returns are affected by the variables are measured due to the “premium” coefficients, thus responsible for the direction and strength the variable possesses on the portfolio or asset returns. In addition, an abundance of scientists applied the Fama-Macbeth procedure to test for size effects as for instance Reinganum (1982) and Zarowin (1990).

In the preceding section 3 hypotheses are described, these hypotheses require separate regression tests. At first the returns predicted by CAPM for the asset or portfolios are measured. Once the excess returns over CAPM are measured the relation of returns to additional risk factors are investigated. The first Fama-MacBeth regression is conducted to test for the size- effect. If small stocks indeed outperform large stocks in terms of return the existence of the size-effect holds for the European sample in this thesis. The second Fama-MacBeth regression aims to find whether higher dividend yields contributes to higher returns. The Fama-Macbeth procedure in general consists of two separate regressions, as is the case here. Step 1 is described below in methodological format. Step 1 takes into account the monthly excess asset returns over CAPM predictions, and determines the time-series sensitivity of the excess returns to the risk factor with estimate $\hat{\beta}^k$.

$$(6)\ R_{n,t} = \alpha_n + \beta_{n,F1}F_{1,t} + \cdots + \beta_{n,FR}F_{r,t} + \varepsilon_{n,t}$$

The excess return of securities $R_{n,t}$ is on the left side of equation six, and regressed on one or more risk factors $F_{r,t}$. In total there are T periods, the sensitivity of securities to the risk factor(s) are measured with coefficient $\hat{\beta}_{n,Fr}$. Sample estimations are measured because “true” population parameters are not available. Applying the following formulas, the beta as well as standard errors are computed.

$$(7)\ \hat{\beta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t^k$$

$$(8)\ \sigma^2\left(\hat{\beta}^{\,k}\right) = \frac{1}{T(T-1)}\sum_{t=1}^{T}(\hat{\beta}_t^k - \hat{\beta}^k)^2$$

Once the time-series estimates of beta $\hat{\beta}$ for the entire sample are measured they are applied in a cross-sectional framework. Each month of the sample separate cross-sectional regressions are conducted.

$$(9)\ R_{i,t} = \alpha_T + \gamma_{n,F1}\hat{\beta}_{1,t} + \cdots + \gamma_{r,T}\hat{\beta}_{i,,Fr} + \varepsilon_t$$

$R_{i,t}$is once again in excess over CAPM predictions. In the second step of the Fama-MacBeth procedure the aim is to find whether a larger factor loading $\hat{\beta}^k$ of step 1 implies higher asset or portfolio returns. The strength of regression coefficient $\gamma_{r,T}$ on $R_{i,t}$ provides information whether higher factor loadings indeed contribute to higher returns. To measure the "risk premium" of the factor(s) for the entire sample, the regression coefficients $\gamma_{r,T}$ for each month $t$ in the sample are averaged. Averaging the coefficients $\gamma_{r,T}$ over the T-periods measures the risk premium for the chosen factor accompanied by a T-test:

$$(10)\ \frac{\gamma_k}{\sigma_{\gamma,k}/\sqrt{T}}$$

In the formula $\sigma_{\gamma,k}$ is the standard error of the $\gamma_{k,t}$ coefficients. The outcomes of the T-tests are used to assess the hypotheses related to size-and dividend yield effects on returns. A common issue with the Fam-MacBeth approach, due to the two-pass regression, is that the error terms in formula 9 suffer from autocorrelation. Newey-West standard errors are applied in the second regression of the procedure to prevent autocorrelation. In addition, to be able to translate the T-test outcomes of the coefficients without modifications, the test is standardized with a mean of zero and standard errors are set at unit. Each "unit" of increase in the standard deviation causes returns to increase with the exact coefficient estimate.

### 4.2.2 Portfolio sorting & excess return computation

In the preceding section the excess returns over CAPM are mentioned as the dependent variable in the procedure. To compute the returns estimated with CAPM and thus the excess returns in the Fama-MacBeth procedure, estimates of market betas are necessary for the different portfolios. As aforementioned, portfolio estimates of beta appear to be superior to individual estimates in terms of preciseness and limiting error in variables. Hence, portfolios rather than individual stocks are used to compute market betas. Especially, Fama and French (1992) introduced inventive sorting techniques in order to compute portfolio betas. For that reason, this thesis follows Fama and French (1992). Before Fama and French (1992) sorting stocks into size portfolios was supposed suffices in generating spread between average returns and market betas. A problem with this univariate sorting is that size and market beta are nearly perfect correlated (Fama and French, 1992) which makes it hard to distinguish between beta and size effects.

In addition, one can imagine that when for instance an electricity company and zoo possess the same market capitalization, according to their same size class with univariate sorting they will have the same portfolio beta assigned. In reality however, their betas vary widely due to differing line of business. Estimates of portfolio betas are then very different from “true” individual beta. Fama and French (1992) aim to solve the issue using “Pre-Ranked” individual betas when assigning stocks to size-and thus beta portfolios. The ten size deciles are now subdivided in ten pre-ranked beta portfolios, creating 10x10 hundred size-beta portfolios. A rule of thumb is that investors should compose their portfolios at a minimum of 15-20 stocks. To be able to attain the minimum level of 15 stocks for every portfolio applied in this thesis Fama and French (1992) is adjusted. Beta quintiles instead of deciles makes sure that every portfolio obtains the minimum amount of stock, creating 10x5 fifty size-beta portfolios.  36 months of return data are supposed to suffice in order to produce a stable beta (Fama and French, 1992). The individual stock returns in the preceding 36 months before February year $t$ are regressed on the MSCI Europe returns, both are in excess of the risk-free rate. The pre-ranked beta is then calculated as the sum of the slope coefficients on the contemporaneous and once-lagged market return of the MSCI. Thereafter, the pre-ranked betas are assigned to the size-beta portfolios. Every year $t$ the process is repeated, which ensures that stocks can move between portfolios. From March to February in every year $t$, the equal-weighted portfolio returns are computed.

The equal-weighted portfolio returns are used to compute the marker betas, once the the portfolio market betas are estimated they are assigned to individual stocks. Resulting in the individual post-ranking sum beta. According to Fama and French (1992) there is no reason to prefer portfolios over individual stocks in the Fama-MacBeth procedure. Whilst applying individual measurements firm-specific info is maintained. So, for each individual stock the monthly CAPM predicted returns are computed with the assigned market beta. The dependent variable in the FamaMac-Beth procedure is then found by subtracting the monthly CAPM predicted return of the actual return.

In order to minimalize the aforementioned issue of non-synchronous trading, a lag in the MSCI Europe index return is added in computation of the portfolio betas. Many scientists as Dismon (1979) and Cohen et al. (1983) propose a lag in the market return.

$$(11)\ R_{i,t} = \alpha_n + \beta_i R_{M,t} + \beta_i R_{M,t-1} + \varepsilon_{i,t}$$

The MSCI Europe Index is the best available benchmark with regard to the European dataset in this research. It comprises 15 countries and is able to cover 85% of the market cap of these countries. In addition, the index return is value-weighted.

### 4.2.3 Regression models

In order to test the hypotheses of section 4.1 with the aim of answering the research question, the following models are created:

*1a)" Small firms earn on average higher excess returns over large firms listed on the European market"*
*1b)" Hypothesis 1a is robust to the January effect"*

$$(A) \quad R_{Excess_{i,t}} = \alpha_i + \beta_1 Size_{i,t} + \varepsilon_{i,t}$$

*2) "Firms with higher dividends earn excess returns over firms with lower dividend"*

$$(B) \quad R_{Excess_{i,t}} = \alpha_i + \beta_1 DY_{i,t} + \varepsilon_{i,t}$$

*3)" Once controlled for dividend yields, there are no excess returns with regard to size"*

$$(C) \; R_{Excess_{i,t}} = \alpha_i + \beta_1 Size_{i,t} + \beta_2 DY_{i,t} + \varepsilon_{i,t}$$

| | |
|---|---|
| $R_{Excess_{i,t}}$ | = Monthly excess return of security *i* |
| $\alpha_i$ | = Constant term |
| $Size_{i,t}$ | = Natural log of market cap of security *i* |
| $DY_{i,t}$ | = Dividend yield of security *i* |
| $\varepsilon_{i,t}$ | = Error term |

The dependent variable $R_{Excess_{i,t}}$ is the excess return of asset *i* in month *t*. Excess return is characterized as the premium over CAPM, computed by subtracting the CAPM estimated return of the actual return of asset *i* in month *t*. The CAPM return is estimated as:

$$(12) \; R_{CAPM} = rf_t + \beta_I \left(R_m - rf_t\right)$$

In the formula $\beta_I$ refers to post-ranking beta of security *i* in month *t*, which is part of size-beta portfolio I. $rf_t$ is the risk-free rate, in this thesis the monthly return on a 10 year German government is applied. Due to its stability and European origin. $R_m$ is the market return, as mentioned in the previous section the value-weighted MSCI Europe Index mimics the market in this thesis. Now that it is clear how the CAPM return is estimated, excess return can be computed:

$$(13) \quad R_{Excess_{i,t}} = R_{actual_{i,t}} - R_{CAPM_{i,t}}$$

The independent variable $Size_{i,t}$ is the natural logarithm of market capitalization of security $i$ in month *t.* It is computed by multiplying the number of shares outstanding times the price at the end of each month. The second independent variable is $DY_{i,t}$, dividend yield, of security $i$ in month *t.* As aforementioned, the variable is similar used as compared to the analysis of de Moor & Sercu (2013). To measure the variable, one needs to divide the dividends per share by the share price. As holds for all the variables, monthly observations are applied.

**4.2.4 Data & Sample**

Thomson Reuters Datastream is used for all company-and market information. In order to assemble a reliable dataset, multiple modifications are made to the initial sample. Fama and French (1992) argue that 36 months of return data is sufficient for estimating a reliable beta. If companies do not have 36 months of return data prior to March 1999, they are removed from the sample. If datastream does not report continuously on monthly stock prices, market cap or dividend yield the stocks are deleted from the sample. When datastream fails to report due to delisting of the company, the listed observations are still used in the sample.

An abundance of academics discovered that often so called “penny stocks” are drivers of the premiums found for very small size deciles, these “penny” observations are excluded from the monthly firm observations. These very small firms suffer from illiquidity, price pressure and price manipulation(Amihud,2002). It is harmful to the analysis if a potential size effect is driven by these inconvenient characteristics. Penny observations in this context are referred to monthly stock price observations below 1 €, or a market cap below 10 million €.

De Moor & Sercu (2013) suggest an additional liquidity filter, which is applied in this research. If stocks have zero returns for more than five percent of the number of listed months, they are removed from the sample. On the next page in table 1 the adjustments made to the initial sample are visible. 2184 companies are subject to the final sample. The modifications are not complementary. For example, an illiquid security could also be a penny stock.

To prevent survivorship bias, securities that are delisted before February 2017 are nevertheless included in the regression. A minimum of 36 months of return data is required for the listed months. In addition, there are no modifications made to the sample to appropriate for delisting. Because the effect of delisting on returns is rather arbitrary, it could be positive or negative. Especially, datastream does not mention the reason for delisting, making it hard to correct for potential delisting bias in returns.

In order to use the dataset, a couple of statistical checks are necessary. Because the dataset is very large, normality-tests as the Anderson-Darling as well as the Lilliefors are irrelevant, due to the fact that they always will reject normality. To see if there is any multicollinearity between the variables, a correlation matrix is added to the appendix. Newey-west standard errors are applied in the FM-regressions to prevent for autocorrelation and heteroscedasticity.

**Table 1**
**Sample adjustments**

Table 1 provides an overview of the initial sample and the adjustments made to it. Stocks for which there was no information on either price, return, size or dividend yield are removed from the sample. Stocks with zero returns on more than 5% of the listed months are regarded as illiquid and therefore deleted. Penny stocks are securities with a price below 1€ , or a market cap below 10 million € , and are disregarded in the final sample.

| | |
|---|---|
| Initial dataset | 10815 |
| Penny Stocks | X |
| Illiquid securities | X |
| Securities lacking information | X |
| Securities with less than 36 months of return data(prior march 1999) | X |
| Smallest firms with market cap below 10M | X |
| Final set | 2184 |

### 4.2.5 Subsamples

As a robustness check and to detect any variation in time, subsamples are created. The dataset is subdivided into four subsamples. Which are selected due to economic circumstances during the timeframe.

1) Post-dotcom bubble (August 2000- August 2003)
2) Economic boom prior to crisis (September 2003- March 2008)
3) Credit crunch (April 2008- July 2010)
4) Post- credit crunch (August 2010- February 2017)

Although the selection of subsample periods remains rather arbitrary, it will, in combination with the large dataset add to the reliability of the results in this thesis.

## 5. Analysis of regression results

The previous chapter focused on methodology. Now the methodology is brought into practice, testing the formulated hypotheses and analyzing their results. To get acquainted with the dataset and show how the risk factors are related to excess returns the first part of this section gives an overview of the descriptive statistics. Followed by the results of the Fama-MacBeth regressions for the period March 1999 to February 2017.

### 5.1 Descriptive statistics

Table 2(see next page) provides the descriptive statistics of the full sample. The sample consists of 16 countries, covering Europe. The column # Firms gives the number of firms per country that, at any given moment, participated in the dataset for the period March 1999 to February 2017. 36 months of return data is required for securities to take part. In addition, stocks that are delisted are nevertheless included in the sample. The first row of the column displays the number of firms for Europe, 2184 in total. The column after #Firms, is dedicated to the return variable. The return variable is the average monthly return per country. Belgium is allotted with the lowest average monthly return of -0.01%, opposite to Sweden, which has the highest average monthly return of

1.19%. The excess returns are computed by subtracting the CAPM estimated return of the actual return. The CAPM estimated return is measured with post-raking sum beta. Except for Sweden and the U.K, the same pattern is occurring. The CAPM return is a positive amount, which results in excess return to be a smaller number than actual return. Only for Belgium excess return is a negative number, this is due to the fact the actual return already was a negative number. Surprisingly is the negative CAPM return for Sweden and the U.K, resulting in a larger number for excess return than for actual return.

**Table 2**
**Descriptive statistics full sample**

Table 2 displays the sample characteristics of the 16 countries covering Europe. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio retums on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coefficients of return on contemporeanous and lagged weighted MSCI Europe Index return. Size is measured as the natural logarithm of the variable.

| | | Return | | Excess Return | | Beta | | | Sum beta | | | SIZE | | DIV.YIELD | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Region | # Firms | Mean | SD | Mean | SD | Mean | SD | Median | Mean | SD | Median | Mean | SD | Mean | SD |
| Europe | 2184 | 0.72 | 10.29 | 0.61 | 10.83 | 0.07 | 0.30 | 0.01 | 0.59 | 0.85 | 0.63 | 6.05 | 2.17 | 2.80 | 8.83 |
| *Country:* | | | | | | | | | | | | | | | |
| Austria | 44 | 0.85 | 9.92 | 0.60 | 10.65 | 0.09 | 0.33 | 0.02 | 0.61 | 0.86 | 0.64 | 6.30 | 1.72 | 2.37 | 2.61 |
| Belgium | 76 | (0.01) | 4.49 | (0.44) | 4.74 | (0.04) | 0.15 | (0.05) | 0.26 | 0.36 | 0.22 | 2.74 | 0.05 | 2.78 | 5.54 |
| Denmark | 81 | 0.86 | 11.86 | 0.85 | 12.21 | 0.05 | 0.27 | 0.00 | 0.53 | 0.77 | 0.53 | 5.70 | 1.83 | 2.06 | 3.61 |
| Finland | 80 | 0.83 | 9.56 | 0.70 | 10.14 | 0.08 | 0.28 | 0.03 | 0.61 | 0.82 | 0.69 | 6.03 | 2.04 | 3.98 | 11.08 |
| France | 282 | 0.65 | 11.59 | 0.51 | 81.67 | 0.07 | 0.30 | 0.02 | 0.59 | 0.83 | 0.64 | 6.08 | 2.09 | 2.91 | 3.86 |
| Germany | 406 | 0.86 | 11.53 | 0.61 | 12.08 | 0.09 | 0.32 | 0.03 | 0.63 | 0.91 | 0.67 | 5.68 | 2.11 | 2.29 | 6.15 |
| Ireland | 20 | 0.65 | 11.59 | 0.40 | 12.32 | 0.09 | 0.31 | 0.03 | 0.66 | 0.89 | 0.71 | 7.16 | 1.53 | 2.05 | 5.83 |
| Italy | 164 | 0.19 | 10.88 | 0.12 | 11.46 | 0.08 | 0.29 | 0.03 | 0.58 | 0.86 | 0.71 | 5.93 | 1.91 | 0.12 | 11.46 |
| Luxembourg | 7 | 0.68 | 10.53 | 0.67 | 11.13 | 0.10 | 0.34 | 0.03 | 0.64 | 1.00 | 0.45 | 6.99 | 1.16 | 0.67 | 11.13 |
| Netherlands | 86 | 0.47 | 10.48 | 0.42 | 11.03 | 0.08 | 0.30 | 0.02 | 0.64 | 0.87 | 0.69 | 6.47 | 2.14 | 0.42 | 11.03 |
| Norway | 70 | 0.93 | 11.14 | 0.72 | 11.65 | 0.10 | 0.31 | 0.03 | 0.64 | 0.89 | 0.67 | 5.96 | 1.78 | 0.72 | 11.65 |
| Portugal | 15 | 0.28 | 9.29 | 0.10 | 9.79 | 0.05 | 0.27 | 0.00 | 0.56 | 0.83 | 0.71 | 7.11 | 1.53 | 0.10 | 9.79 |
| Spain | 66 | 0.39 | 9.17 | 0.27 | 10.02 | 0.08 | 0.31 | 0.02 | 0.62 | 0.85 | 0.71 | 7.20 | 2.11 | 0.27 | 10.02 |
| Sweden | 191 | 1.19 | 11.04 | 1.23 | 11.61 | 0.13 | 0.32 | 0.07 | 0.73 | 0.90 | 0.79 | 5.98 | 1.96 | 1.23 | 11.61 |
| Switzerland | 236 | 0.84 | 8.71 | 0.68 | 9.21 | 0.03 | 0.29 | (0.03) | 0.47 | 0.80 | 0.42 | 6.34 | 1.86 | 3.06 | 19.15 |
| U.K | 369 | 0.79 | 10.34 | 0.86 | 10.84 | 0.07 | 0.29 | 0.08 | 0.58 | 0.83 | 0.64 | 6.78 | 1.98 | 3.08 | 3.12 |

A reason for these unexpected outcomes could be that fortuitously a relative large portion of securities in these countries have the combination of a high sum beta in combination with a negative market return. This will result in a highly negative CAPM return. Apparently, the distribution of CAPM returns is to such a degree affected that the average CAPM return turned negative for the U.K and Sweden.

The average sum beta is 0.59. One should expect this number to be closer to 1. A beta of one would imply a perfect fit between the dataset and the market. In this case however, the countries hypothesized to mimic Europe move substantially different from the Europe MSCI Index. The low average beta of 0.07 is due to the time lag used in the regression.

Table 3 provides the descriptive statistics for the size sorted portfolios. In line with academic papers as the Moor & Sercu (2013) smaller companies have higher returns. However, as is evident from table 3 the pattern is non-monotonic. For example, the fourth size decile has a higher return than the third size decile. Although, on average there is a declining trend of return relative to size. In table 4 the descriptive statistics of the dividend yield sorted portfolios are given. Except for the zero-dividend yield portfolio, return decreases when dividend yield increases. Implying a negative relationship between dividend yield and return. This does not tally with the U-shaped pattern described in the literature review. Which has much support in academic papers.

**Table 3**
**Sample characteristics for size sorted portfolios**

Table 3 displays the means and standard deviations of the sample characteristics for the size sorted portfolios. Each year the stocks are sorted into equally weighted portfolios based on market value. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Pos ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. Size is measured as the natural logarithm of the variable.

| | Return | | Excess Return | | Beta | | Sum beta | | SIZE | | DIV. YIELD | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Size Portfolio | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| | | | ? | | | | | | | | | |
| Size-Small | 0.99 | 18.08 | 0.76 | 18.31 | 0.07 | 0.28 | 0.53 | 0.79 | 3.48 | 0.83 | 2.38 | 12.28 |
| Size-2 | 0.80 | 11.55 | 0.69 | 11.87 | 0.07 | 0.26 | 0.48 | 0.78 | 4.12 | 0.69 | 2.67 | 6.60 |
| Size-3 | 0.65 | 10.82 | 0.66 | 11.50 | 0.06 | 0.29 | 0.52 | 0.82 | 4.68 | 0.66 | 3.02 | 15.97 |
| Size-4 | 0.91 | 10.69 | 0.78 | 11.17 | 0.07 | 0.28 | 0.54 | 0.84 | 5.22 | 0.64 | 2.58 | 3.57 |
| Size-5 | 0.83 | 10.38 | 0.68 | 10.90 | 0.05 | 0.30 | 0.58 | 0.87 | 5.74 | 0.60 | 2.74 | 4.00 |
| Size-6 | 0.81 | 10.15 | 0.73 | 10.63 | 0.07 | 0.28 | 0.60 | 0.82 | 6.29 | 0.59 | 2.85 | 3.58 |
| Size-7 | 0.87 | 9.85 | 0.80 | 10.39 | 0.08 | 0.33 | 0.63 | 0.82 | 6.86 | 0.60 | 3.15 | 14.23 |
| Size-8 | 0.65 | 9.50 | 0.64 | 10.25 | 0.10 | 0.31 | 0.67 | 0.90 | 7.47 | 0.66 | 2.61 | 2.73 |
| Size-9 | 0.63 | 8.93 | 0.53 | 9.64 | 0.08 | 0.32 | 0.67 | 0.89 | 8.31 | 0.80 | 2.90 | 8.20 |
| Size-Large | 0.44 | 8.79 | 0.27 | 9.53 | 0.09 | 0.34 | 0.68 | 0.90 | 9.71 | 1.37 | 3.09 | .96 |

**Table 4**
**Sample characteristics for dividend yield sorted portfolios**

Table 4 displays the means and standard deviations of the sample characteristics for the dividend yield sorted portfolios. Each year the stocks are sorted into equally weighted portfolios based on dividend yield. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. Size is measured as the natural logarithm of the variable.

| | Return | | Excess Return | | Beta | | Sum beta | | SIZE | | DIV.YIELD | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dividend Yield Portfolio | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| | | | ? | | | | | | | | | |
| Dividend Yield-Zero | 0.82 | 16.34 | 0.63 | 16.75 | 0.12 | 0.32 | 0.69 | 0.96 | 5.06 | 1.69 | 0.00 | 0.00 |
| Dividend Yield-Small | 1.88 | 9.84 | 1.39 | 10.82 | 0.05 | 0.26 | 0.77 | 0.83 | 6.49 | 1.89 | 0.44 | 0 .25 |
| Dividend Yield-2 | 1.88 | 9.07 | 1.57 | 9.65 | 0.07 | 0.30 | 0.56 | 0.87 | 6.64 | 1.89 | 1.16 | 0.17 |
| Dividend Yield-3 | 1.61 | 8.66 | 1.41 | 9.24 | 0.07 | 0.30 | 0.55 | 0.84 | 6.72 | 1.94 | 1.67 | 0.13 |
| Dividend Yield-4 | 1.36 | 8.44 | 1.27 | 9.06 | 0.07 | 0.31 | 0.54 | 0.83 | 6.67 | 1.98 | 2.12 | 0.13 |
| Dividend Yield-5 | 1.08 | 9.27 | 1.00 | 9.81 | 0.06 | 0.31 | 0.53 | 0.82 | 6.72 | 1.94 | 2.57 | 0.13 |
| Dividend Yield-6 | 0.80 | 8.33 | 0.78 | 8.88 | 0.06 | 0.31 | 0.51 | 0.81 | 6.67 | 1.98 | 3.05 | 0.15 |
| Dividend Yield-7 | 0.61 | 8.33 | 0.57 | 8.86 | 0.06 | 0.32 | 0.50 | 0.80 | 6.60 | 1.99 | 3.60 | 0.17 |
| Dividend Yield-8 | 0.23 | 8.41 | 0.36 | 8.85 | 0.36 | 8.85 | 0.51 | 0.78 | 6.52 | 1.99 | 4.28 | 0.23 |
| Dividend Yield-9 | (0.23) | 9.05 | (0.12) | 9.55 | 0.06 | 0.29 | 0.56 | 0.76 | 6.31 | 2.08 | 5.31 | 0.40 |
| Dividend Yield-Large | (1.84) | 12.24 | (1.66) | 12.72 | 0.06 | 0.29 | 0.61 | 0.77 | 5.79 | 2.01 | 11.35 | 29.58 |

## 5.2 Regression results

Now the results of the monthly Fama-MacBeth regressions are discussed. Each month the excess returns over CAPM are regressed on size and dividend yield, in univariate as well as multivariate cross-sectional regressions. The first column of the regression table gives the coefficient, which corresponds to the risk premium for the variable. The table is completed with the standard error and t-statistic of the coefficient.

### 5.2.1 Excess return and size

In section 4.1.1 the hypothesis whether small cap stocks outperform large cap, on average, is discussed. In practice, the hypothesis is tested by a regression of excess return on the natural logarithm of market capitalization. In table 5 the regression results are displayed. Contrary to expectations, many countries show evidence for a reversed size effect. Europe as a whole has a positive coefficient of 0.08, which is significant at the 5% level. Implying that excess return increases with the natural logarithm of market capitalization. The reversed size effect is most pronounced in the U.K and Finland. With t-statistics of 5.3 and 10.1, respectively. Both significant at the 1% level. Only in Portugal there is a significant size effect, a coefficient of -0.29 which is significant at the 5% level. The size effect implies that there is a premium for smaller stocks relative to large cap stocks.

A lot of academics claim the size effect to be mostly present in January months. Referring to section 4.1.1, van Dijk(2011) founds an extraordinary peak of the size premium for January months in the 20$^{th}$ century in the U.S. To analyze whether the European dataset of this thesis is subject to seasonality in stock returns, panel A of table 6 is created. The first row of table 6 panel A corresponds to the results for Europe in table 5.  Implying a reversed size effect for the full sample. Row 2 and 3 of Panel A are dedicated to seasonality. Unexpectedly, there is a reversed size effect in January months as opposite to a size premium for non-January months. Both coefficients are insignificant, and thus meaningless in terms of causality.

To improve robustness of the results several subsamples are developed. Panel B of table 6 displays the average coefficients of the four subsamples. All the coefficients are positive, which is in line with the reversed-size effect for Europe. Once again, the coefficients are insignificant. Taking into account the results of Table 5 and 6, one should reject Hypothesis 1A and 1B. There is no evidence for existence of a size premium in Europe. When only focusing on January months the same holds true.

**Table 5**
**Regression analysis of the relationship between excess return and size per country**

Table 5 displays the results of montlhy cross-sectional Fama-Macbeth regressions of individual excess stock returns on the natural logarith of market capitalization. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. The regression is performed with Newey-West standard errors for the period March 1999 to February 2017.

| | SIZE | | | INTERCEPT | | |
|---|---|---|---|---|---|---|
| Region | Coef | SE | T-stat | Coef | SE | T-stat |
| Europe | 0.08 | 0.04 | 2.01** | 0.17 | 0.34 | 0.49 |
| *Country:* | | | | | | |
| Austria | 0.26 | 0.10 | 2.49** | (1.03) | 0.63 | (1.64) |
| Belgium | 0.22 | 0.05 | 3.99*** | (1.11) | 0.08 | (12.78)*** |
| Denmark | 0.20 | 0.08 | 2.37** | (0.30) | 0.62 | (0.48) |
| Finland | 1.28 | 0.13 | 10.14*** | (4.69) | 0.61 | (7.67)*** |
| France | 0.04 | 0.05 | 0.94 | 0.02 | 0.04 | 0.56 |
| Germany | 0.11 | 0.05 | 2.22** | (0.09) | 0.39 | (0.24) |
| Ireland | 0.56 | 0.20 | 2.86*** | (0.36) | 0.15 | (2.36**) |
| Italy | 0.12 | 0.056 | 2.15** | (0.56) | 0.56 | (1.01) |
| Luxembourg | (0.06) | 0.37 | (0.17) | 0.92 | 2.93 | 0.31 |
| Netherlands | 0.11 | 0.05 | 2.00** | (0.32) | 0.47 | (0.70) |
| Norway | 0.14 | 0.10 | 1.38 | (0.08) | 0.51 | (0.16) |
| Portugal | (0.29) | 0.13 | (2.19)** | 2.31 | 1.13 | 1.88* |
| Spain | 0.03 | 0.06 | 0.39 | 0.01 | 0.61 | 0.02 |
| Sweden | 0.04 | 0.06 | 0.68 | 0.10 | 0.57 | 1.66* |
| Switzerland | 0.11 | 0.05 | 2.43** | (0.16) | 0.34 | (0.46) |
| U.K | 5.83 | 1.10 | 5.30*** | (-26.24) | (-5.13) | (-5.12)*** |

* Significant at 10%
** Significant at 5%
***Significant at 1%

**Table 6**
**Regression analysis of the relationship between excess return and size by month and period**

Table 6 displays the results of montlhy cross-sectional Fama-MacBeth regressions of individual excess stock returns on the natural logarith of market capitalization. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. The regression is performed with Newey-West standard errors for the period march 1999 to february 2017. Panel A gives an overview of the average coefficents of the regression with regard to subsamples of January and non-January months. Panel B is dedicated to subsamples based on economic time frames.

| | SIZE | | | INTERCEPT | | |
|---|---|---|---|---|---|---|
| Portfolio | Coef | SE | T-stat | Coef | SE | T-stat |
| Panel A | | | | | | |
| All Months | 0.08 | 0.04 | 2.01** | 0.17 | 0.34 | 0.49 |
| January | 0.24 | 0.15 | 1.55 | 0.44 | 0.69 | 0.64 |
| Non-january | (0.11) | 0.08 | (1.33) | 1.71 | 0.79 | 2.14** |
| Panel B | | | | | | |
| Post-dotcom bubble *2000-2003* | 0.30 | 0.34 | 0.88 | 0.46 | 2.61 | 0.17 |
| Boom prior to crisis *2003-2008* | 0.28 | 0.35 | 0.81 | 0.58 | 2.64 | 0.22 |
| Credit crunch *2008-2010* | 0.19 | 0.13 | 0.13 | (0.74) | 1.64 | (0.45) |
| Post-credit crunch *2010-2017* | 0.05 | 0.05 | 0.84 | 0.24 | 0.45 | 0.51 |

* Significant at 10%
** Significant at 5%
***Significant at 1%

### 5.2.2 Excess Return and dividend yield

Hypothesis 2 is formulated with the idea that firms with higher dividend yield earn excess returns over firms with lower dividend yield. Especially, the result of the Moor & Sercu (2013) motivated to formulate hypothesis 2 this particular way. In their research the coefficient for $DY_{i,t}$ is positive for all the size deciles (See Appendix), except for the third and largest size decile all the coefficients are also significant. Implying that an increase in dividend yield leads to higher risk-adjusted returns.

The terminology of de Moor & Sercu (2013) in the case of risk-adjusted returns, as opposite to the formulation of excess returns in this research as well as application of portfolio returns instead of individual-firm returns in the regression analysis are the essential differences between De Moor & Sercu (2013) and this research. Despite the deviations in methodology, there is sufficient resemblance to expect results that are at least to some part in line with each other. For example, it should make no substantial difference with regard to results whether firms are combined in portfolios or analyzed separately. In addition, de Moor & Sercu (2013) apply an extended version of CAPM whilst computing excess or risk-adjusted returns. Off course these differing measurement techniques compared to this thesis have impact on results. Nevertheless, one expects similarities.

**Table 7**
**Regression analysis of the relationship between excess return and dividend yield per country**

Table 7 displays the results of montlhy cross-sectional Fama-Macbeth regressions of individual excess stock returns on the natural logarith of market capitalization. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. The regression is performed with Newey-West standard errors for the period March 1999 to February 2017.

| | DY | | | INTERCEPT | | |
|---|---|---|---|---|---|---|
| Region | Coef | SE | T-stat | Coef | SE | T-stat |
| Europe | (15.14) | 2.24 | (6.77)*** | 1.13 | 0.36 | 3.16*** |
| *Country:* | | | | | | |
| Austria | (25.13) | 7.02 | 3.58*** | 1.17 | 0.44 | 2.65*** |
| Belgium | (20.34) | 8.06 | (2.52)** | 0.76 | 0.44 | 1.73** |
| Denmark | (15.74) | 3.62 | (4.34)*** | 1.26 | 0.38 | 3.30*** |
| Finland | (12.58) | 1.96 | (6.41)*** | 1.12 | 0.32 | 3.54*** |
| France | (17.80) | 2.67 | (6.66)*** | 1.11 | 3.76 | 2.95*** |
| Germany | (20.17) | 3.72 | (5.42) | 1.10 | 0.40 | 2.77 |
| Ireland | (2.29) | 11.47 | (0.20) | 0.50 | 0.53 | 0.95 |
| Italy | (20.99) | 6.88 | (3.05)*** | 0.63 | 0.47 | 1.33 |
| Luxembourg | (84.16) | 34.96 | (2.41)** | 1.33 | 0.56 | 2.39 |
| Netherlands | (16.32) | 4.76 | (3.43)*** | 1.05 | 0.43 | 2.44** |
| Norway | (18.38) | 5.11 | (3.59)*** | 1.40 | 0.53 | 2.62*** |
| Portugal | (33.72) | 26.94 | (1.25) | 0.79 | 0.53 | 1.49 |
| Spain | (10.12) | 7.41 | (1.37) | 0.58 | 0.46 | 1.28 |
| Sweden | (29.23) | 9.77 | (2.99)*** | 1.95 | 0.53 | 3.68*** |
| Switzerland | (19.66) | 3.89 | (5.04)*** | 1.04 | 0.32 | 3.20*** |
| U.K | (15.33) | 16.96 | (0.90) | 1.62 | 0.50 | 3.22*** |

* Significant at 10%
** Significant at 5%
***Significant at 1%

Taking these arguments into account, the results of table 7 are surprising. All coefficients are negative. Whilst de More & Sercu (2013) report solely positive coefficients for $DY_{i,t}$ .In addition, the majority of countries have coefficients that are negative at the 1% significance level. Europe in total poses a coefficient of -15.14, with a t-value of 6.77 which is significant at the 1% level. With regard to the individual country analysis, France and Finland report the largest t-values of 6.66 and 6.41, respectively. With coefficients of -17.80 for France and -12.58 in the case of Finland, they pose the most significant results. Interestingly, both France and Finland belong to the countries with relatively small coefficients. Due to preciseness in estimation of variable coefficients for France and Finland, their standard error is very low. Hence, despite their small coefficients they still report the most significant results. Looking at the results of table 7, hypothesis 2 is rejected. There is no evidence that firms with higher dividend yield earn excess return over firms with lower dividend yield. To be precise, the reverse holds true. The negative average coefficients, most of them highly significant, imply that firms with lower dividend yield earn excess returns over firms with higher dividend yield.

### 5.2.3 Excess return, size and dividend yield

The third and last hypothesis described in section 4 tests whether dividend yields could be the missing risk factor in case of the size effect. Despite the fact that there was no evidence found of the size premium in Europe, a multivariate regression of size and dividend yield is still relevant with regard to how dividend yields influence the relationship between size and excess return.

In table 8 the results of the regression of excess return on size and dividend yields is visible. Adding dividend yields to the regression analysis doesn't alter the coefficient results very much, for size as well as dividend yield. The majority of countries face a slight decrease in their coefficients. For example, the size coefficient of Europe changes from 0.06 to 0.08. In the case of Austria, the coefficient decreases from 0.26 to 0.25. Oddly, there are also countries who experience it the other way around. Portugal as well as Switzerland encounter increases of 0.02 and 0.06, respectively. In general, the countries who experienced a reversed size effect or size premium still have significant positive premiums for the size coefficient in the regression with dividend yields.

According to my knowledge no other academic papers exists who links dividends to size in a multivariate regression analysis with excess return or risk-adjusted return as the dependent variable. Taking that into account it is impossible to judge whether the results in table 8 are in line with current papers, because the topic is so unexplored.

In table 9 there is an interaction variable $Size_{i,t}$*$DY_{i,t}$ added to the regression analysis. The interaction variable is added to test for the assumption that the relation of excess return and size varies by the amount of dividend yield and that the relation between excess return and dividend yield depends on size. The coefficient of the interaction variable for Europe is -3.19, with a t-value of -3.38 and significant at the 1% level. Most of the average coefficients are negative, and in the case of Austria, Denmark, Netherlands, Sweden and Switzerland also significant. A negative coefficient of the interaction variable implicates that the effect of size on excess return decreases in case the amount of dividend yield of a stock increases. Conversely, it also implicates that when size increases for companies, the effect of dividend yield on excess return decreases.

Summarizing, the ability of dividend yields to explain the size effect seems low according to the results in table 8 & 9. The reversed size effect lives on, the average coefficients for the different countries and Europe as a whole are hardly affected. The interaction term implies that the effect of dividend yields on excess returns decreases for larger companies. Hypothesis 3 thus must be rejected. Although the results advocate a reversed size effect instead of a size premium, the modest or close to zero role of dividend yield explaining size effects is evident.

**Table 8**
**Regression analysis of the relationship between excess return on size and dividend yield**

Table 8 displays the results of montlhy cross-sectional Fama-Macbeth regressions of individual excess stock returns on the natural logarithm of market capitalization and divdend yield. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. The regression is performed with Newey-West standard errors for the period March 1999 to February 2017.

| | SIZE | | | DY | | | INTERCEPT | | |
|---|---|---|---|---|---|---|---|---|---|
| Region | Coef | SE | T-stat | Coef | SE | T-stat | Coef | SE | T-stat |
| Europe | 0.06 | 0.04 | 1.74* | (14.26) | 2.28 | (6.26)* | 0.69 | 0.35 | 1.96* |
| *Country:* | | | | | | | | | |
| Austria | 0.25 | 0.11 | 2.36** | (24.05) | 7.57 | (3.18)*** | 0.40 | 0.69 | (0.57) |
| Belgium | 0.09 | 0.09 | 1.08 | (13.50) | 7.74 | (1.74)** | (0.11) | 0.57 | (0.19) |
| Denmark | 0.15 | 0.08 | 1.83** | (15.22) | 3.52 | (4.32)*** | 0.37 | 0.63 | 0.59 |
| Finland | 1.26 | 0.12 | 10.34*** | (10.83) | 1.84 | (5.89) | (4.19) | 5.93 | (5.89) |
| France | 0.03 | 0.05 | 0.59 | (17.29) | 2.65 | (6.52)*** | 0.91 | 0.41 | 2.22** |
| Germany | 0.08 | 0.05 | 1.61 | (20.18) | 4.06 | (4.97)*** | 0.62 | 0.43 | 1.45 |
| Ireland | 0.55 | 0.21 | 2.72*** | (0.81) | 12.40 | (0.07) | (3.43) | 1.58 | (2.18) |
| Italy | 0.14 | 0.06 | 2.57** | (23.79) | 6.64 | (3.59) | (0.16) | 0.59 | (0.26) |
| Luxembourg | (1.28) | 1.14 | (1.12) | (126.78) | 108.27 | (1.50) | 10.21 | 9.10 | 1.12 |
| Netherlands | 0.08 | 0.05 | 1.35 | (16.16) | 5.02 | (3.22)*** | 0.52 | 0.55 | 0.94 |
| Norway | 0.11 | 0.09 | 1.17 | (15.05) | 4.90 | (3.07)*** | 0.57 | 0.59 | 0.97 |
| Portugal | (0.27) | 0.15 | (1.83)** | (6.70) | 29.20 | (0.23) | 2.32 | 1.18 | 1.96** |
| Spain | 0.03 | 0.07 | 0.43 | (6.99) | 7.25 | (0.96) | 0.27 | 0.64 | 0.43 |
| Sweden | 0.07 | 0.06 | 1.09 | (40.99) | 10.73 | (3.82)*** | 1.55 | 0.66 | 2.35 |
| Switzerland | 0.17 | 0.03 | 4.23*** | (15.82) | 3.30 | (4.78)*** | (0.15) | 0.23 | (0.66) |
| U.K | 5.42 | 1.14 | 4.74*** | (10.95) | 15.73 | (0.70) | (23.96) | 5.46 | (4.39)*** |

* Significant at 10%
** Significant at 5%
***Significant at 1%

**Table 9**
**Regression analysis of the relationship between excess return on size, dividend yield and an interaction variable**

Table 9 displays the results of montlhy cross-sectional Fama-Macbeth regressions of individual excess stock returns on the natural logarithm of market capitalization, dividend yield and an interaction variable of the two. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks.The post-ranking betas are computed as the regression slope of equally weighted portfolio retums on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return. The regression is performed with Newey-West standard errors for the period March 1999 to February 2017.

| | SIZE | | | DY | | | SIZE*DY | | | INTERCEPT | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Region | Coef | SE | T-stat | Coef | SE | T-stat | Coef | SE | T-stat | Coef | SE | T-stat |
| Europe | 0.16 | 0.04 | 3.52*** | 0.78 | 4.40 | 0.18 | (3.19) | 0.95 | (3.38)*** | 0.26 | 0.36 | 0.72 |
| *Country:* | | | | | | | | | | | | |
| Austria | 0.56 | 0.16 | 3.61*** | 50.29 | 26.86 | 1.87* | (12.73) | 4.87 | (2.61)*** | (0.217) | 0.91 | (2.34)** |
| Belgium | 0.49 | 0.22 | 2.27** | 28.57 | 40.31 | 0.71 | (8.88) | (6.61) | (1.34) | (2.13) | 1.21 | (1.76)** |
| Denmark | 0.26 | 0.09 | 2.86*** | 22.32 | 12.47** | 1.79** | (6.75) | (2.38) | (2.83)** | (0.29) | 0.67 | (0.43) |
| Finland | 1.40 | 0.16 | 8.96*** | 20.66 | 10.09 | 2.05** | (7.48) | 2.39 | (3.13) | (4.79) | 0.74 | (6.52)*** |
| France | 0.82 | 0.71 | 1.16 | (6.93) | 8.56 | (0.81) | (1.79) | 1.64 | (1.10) | 6.31 | 4.72 | 1.34 |
| Germany | 1.37 | 0.07 | 2.10** | (11.37) | 9.77 | (1.16) | (1.97) | 1.75 | (1.13) | 0.39 | 0.48 | 0.81 |
| Ireland | 0.61 | 0.30 | 2.02** | 50.39 | 89.44 | 0.56 | (4.45) | 12.30 | (0.36) | (4.02) | 2.29 | (1.75) |
| Italy | 0.21 | 0.08 | 2.69*** | (7.47) | 34.56 | (0.22) | (2.78) | (4.51) | (0.62) | (0.50) | 0.64 | (0.77) |
| Luxembourg | (10.10) | 7.65 | (1.32) | (3000.89) | 2800.30 | (1.09) | 353.60 | 357.73 | 0.99 | 79.49 | 60.12 | 1.32 |
| Netherlands | 0.20 | 0.08 | 2.25** | 18.40 | 13.11 | 1.40 | (6.06) | 2.14 | (2.84)*** | (1.66) | 6.71 | (0.25) |
| Norway | 0.18 | 0.14 | 1.27 | 0.88 | 21.49 | 0.04 | (2.80) | 3.65 | (0.77) | 0.16 | 0.81 | 0.20 |
| Portugal | (0.18) | 0.37 | (0.48) | 101.83 | 154.57 | 0.66 | (14.82) | 20.23 | (0.73) | 1.65 | 2.55 | 0.65 |
| Spain | 0.16 | 0.11 | 1.55 | 26.37 | 30.76 | 0.86 | (4.72) | 4.15 | (1.14) | (0.58) | 0.84 | (0.69) |
| Sweden | 0.28 | 0.08 | 3.40*** | 14.64 | 30.96 | 0.47 | (9.66) | 4.65 | (2.08)** | 4.53 | 6.72 | 0.68 |
| Switzerland | 0.26 | 0.06 | 4.25*** | 16.95 | 8.48 | 2.00** | (6.40) | 1.54 | (4.14)*** | (0.51) | 0.41 | (1.25) |
| U.K | 4.18 | 1.80 | 2.33 | (186.79) | 3.14 | (0.60) | 37.46 | 70.98 | 0.53 | (18.07) | 8.45 | (2.14)** |

* Significant at 10%
** Significant at 5%
***Significant at 1%

### 5.3 Examination of hypotheses

In support of the main research question, several hypotheses are made and tested. In this section, there will be elaborated on the conclusion of these hypotheses.

Hypothesis 1 is twofold, 1a and 1b. 1a is drawn up to test whether a size premium exists in Europe, as well as in the individual European countries for the period March 1999 to February 2017. Hypothesis 1a is formulated as:

*1a)" Small firms earn on average higher excess returns over large firms listed on the European market"*

Taking into account the results of 5.2.1 hypothesis 1a must be rejected. Smaller firms do not earn excess return over large firms. The size coefficient is positive for Europe and almost all individual countries, implying that size contributes positively to excess return. In addition, the subsample analysis does not alter the results. In every single subsample period the size coefficient is positive as well, although the coefficients are insignificant and thus meaningless.

The results of this particular thesis are not in line with the general tendency in academic papers related to size affects, which advocate existence of a size premium for smaller firms. In the literature review, there was elaborated on numerous of these papers. Nevertheless, there are papers that do report existence of a so called "reversed size premium" or absence of size effects. Amihud (2002) for example, reports that multiple periods are subject to absence of size effects. Dimson and March (1999) however, illustrate reversal of the size effect in their paper.

Academics have described many reasons for disappearance of the size effect. Van Dijk (2011) is one of them, he explains that investor behavior dispelled the size premium. In pursuit of profits investors started to trade on the size premium, driving up the prices. Eventually, the increase in prices fades away the size effect. Another explanation by Crain (2011) is based on liquidity. The liquidity of smaller stock has increased over time due to investment funds that particularly started to invest in small cap stocks, which causes small cap stocks to become less risky. The lower risk results in disappearance of the size effect. As described in in section 5, the results of this thesis tend to a reversal of the size effect. A potential explanation for the reversal of the size effect could be that investors are keen to more qualitative investments, for instance due to economic downturns.

Hypothesis 1b is formulated to check if there is any seasonality in stock returns. Because former research claimed the size effect to be particularly present in January, hypothesis 1b is formulated as:

*1b)" Hypothesis 1a is robust to the January effect"*

Hypothesis 1a is rejected, there is no evidence found that smaller firms do earn excess returns over large firms in Europe. To make hypothesis 1a robust to the January effect, the regression is done excluding January months. Surprisingly, excluding January months causes the average coefficient for Europe to turn negative. So, excluding January months results in disappearance of the reversed size effect. To be precise, it results in a regular size premium. Although the negative coefficient is insignificant and thus meaningless. The average coefficient as result of the regression analysis of only January months is positive, indicating that there is a reversed size effect for January months in the sample of this thesis. From the literature review, one expects the size premium to be especially present in January months. So, the results for the January effect found in this thesis are not in line with former academic papers.

Based on the above, hypothesis 1b is rejected. Excluding January observations results indeed to a negative size coefficient, implying that smaller firms earn excess returns over larger firms. But the coefficient is insignificant and thus meaningless.

Now attention is geared towards the relationship of excess returns to dividend yields. Hypothesis 2 is stated as:

*2) "Firms with higher dividend yield earn excess returns over firms with lower dividend yield"*

The results of table 7 section 5.2.2 are striking. All coefficients are negative and most of them significant at the 1% level. Hypothesis 2 is firmly rejected. Firms with higher dividend yield do not earn excess returns over firms with lower dividend yield.

Lastly, hypothesis 3 is scrutinized:

*3)" Once controlled for dividend yields, there are no excess returns with regard to size"*

Adding dividend yields as a control variable in the regression analysis of excess return and size does not influence the relationship between excess return and size very much. The reversed size effect from the univariate regression of size and excess return is still present. Hypothesis 3 therefore must be rejected. Despite the addition of dividend yield to the regression analysis, excess returns with regard to size survive.

# 6. Conclusion, limitations and further research

The next section is focused on the conclusion with regard to the main question and its subparts. Thereafter, the limitations of this research are addresses as well as possibilities for future research.

## 6.1 Conclusion

The principal question of this research was stated in section 1.3 as:

"***To what extent are dividend yields able to explain the relationship between firm size and excess returns for firms listed on the European Market?"***

Contrary to the first size premium test of Banz (1981) as well as later work from Annaert et al. (2002), this thesis founds evidence of a reversed size premium. For the whole sample, March 1999 to February 2017, there is a significant reversed size premium. In the literature review, there are several papers briefly discussed that do report results in favor of a reversed size premium or disappearance of the premium. Dimson and Marsh (1999) for instance, report an extreme reversal of the average yearly U.S size premium comparing the period 1955-1987 to 1988-1997. In addition, Horowitz et al. (2000) report that any relation between size and risk vanished after 1982. Mentioned in section 5.3 there are several reasons that could be responsible for disappearance of the size premium. Increases in liquidity for smaller firms caused by emergence of small-cap investment funds in the eighties (Crain, 2011), traders who exploited the premium too intensely (van Dijk, 2011) and investors who change their portfolio too safer assets during economic downturns, larger companies are in general safer. A much-debated topic in size premium tests is the January effect. Whilst many scientists claim the size premium to be especially present in January months, this thesis couldn't find evidence in favor of seasonal effects.

The relationship of excess return and dividend yield constitutes to the second part of the conclusion. De Moor & Sercu (2013) document a relation between the unexplained-or excess returns of stocks sorted by size with a dividend-yield factor portfolio. They explore a positive relation between size and dividend yield, although dividend yield is not able to fully explain the size effects. Contrary to de Moor & Sercu (2013) this thesis founds a negative relationship between excess returns and dividend yield. For Europe in total the negative coefficient is significant at the 1% level, which is also applicable for several individual countries. Once the dividend yield factor is added to the regression analysis of size and excess return, the effect on size is modest. The reversed size premium is still present in Europe as well as in several individual countries. Although this research finds a reversed size premium instead of a size premium, it is concluded that dividend yields are not able to control for size effects in Europe. Larger companies earn, on average, higher excess returns over smaller firms.

This thesis contributes to current academic papers related to size and dividend yield effects in several ways. Most of the papers which investigate the relation of size and return are outdated and centered on U.S stock returns. The dataset of this thesis is focused on the European market and recent stock returns. In that sense, this thesis fills the gap with existing literature. In addition, this paper provides a clear framework whether dividend yields could be the missing risk factor and a proxy for size effects. The results of this research could be of interest to financial practitioners. Often, there is a small firm premium added whilst computing the cost of equity for companies with CAPM. Taking into account the results of this paper, the small firm premium is biased. Smaller firms do not earn a premium over large firms. So, the cost of equity computation must be adjusted.

### 6.2 Limitations and further research

In this research, (the natural logarithm of) market capitalization is applied as proxy for size. Berk (1995) mentions the potential spurious relation of beginning-of-year market capitalization and subsequent returns, because market capitalization depends on investors' discount rate assumptions. In reaction to this Peek (2015) advocates to apply an alternative measure of firm size whilst constructing size portfolios. The idea of the alternative is that non-market variables as book equity, sales and number of employees together formed in a portfolio, are able to replicate the market capitalization portfolio. The advantage is that the non-market variables are not dependent on investors' discount rate. A limitation of this paper is that only market capitalization is applied as proxy for size, hence the robustness of the results could have been more profound.

As mentioned in section 4.2.2, there is a time lag applied whilst computing the portfolio betas. Many academics as Dismon (1979) and Cohen et al. (1983) propose a lag in the market return, due to its ability to minimalize non-synchronous trading and to eliminate autocorrelation in the residuals (Wilkins, 2018). Achen (2000) however, argues that including a lag in the dependent variable leads to biased coefficient estimates in case there is autocorrelation in the error term. As a result, he advises to exclude lags. A limitation of this thesis is that portfolio betas are only measured with a time lag in the independent variable, improved robustness could be attained by running a regression without a time lag.

Concerning future research, the reversed size premium found in this paper is very interesting. A reversed size premium implicates that current valuation methods, which compensate for a small firm premium, are incorrect. The results of this thesis by itself are too little to demand a paradigm in firm valuation, nevertheless a start is made.

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# 8. Appendix

**Appendix I- Correlation matrix of sample variables**

The table below displays the correlation between the different sample variables for the period March 1999 to February 2017. Excess returns are computed as the premium over CAPM, Post-ranking portfolio betas are based on size-beta sorts using 36 months of return data, and are assigned to the individual stocks. The post-ranking betas are computed as the regression slope of equally weighted portfolio returns on the monthly weighted MSCI Europe Index. Post ranking-sum beta is calculated as the sum of the monthly regression coeeficients of return on contemporeanous and lagged weighted MSCI Europe Index return.

| | Return | Excess Return | Beta | Sum Beta | LNMV | DY |
|---|---|---|---|---|---|---|
| Return | 1.000 | | | | | |
| Excess Return | 0.786 | 1.000 | | | | |
| Beta | 0.000 | 0.007 | 1.000 | | | |
| Sum Beta | 0.004 | (0.025) | 0.139 | 1.000 | | |
| LNMV | 0.023 | 0.026 | 0.045 | 0.076 | 1.000 | |
| DY | (0.042) | (0.037) | (0.011) | (0.014) | (0.013) | 1.000 |

## Appendix II

Table 20

The marginal ability of (zero-)dividend yield to explain the variation over time of portfolio returns classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. The table presents the parameter estimates of the following time-series regressions, one for each portfolio $i$,

$$\alpha_i + \varepsilon_{it} = a_i + d_i DY_{it} + z_i ZDY_{it} + e_{it},$$

where $\alpha_i + \varepsilon_{it}$ is the risk-adjusted return of portfolio $i$ in month $t$ according to the Full model in Table 17, $DY_{it}$ is the equally-weighted (positive) dividend yield of portfolio $i$ in month $t$, and $ZDY_{it}$ is the proportion of zero-dividend yield stocks of portfolio $i$ in month $t$.

| | S | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | B |
|---|---|---|---|---|---|---|---|---|---|---|
| $\hat{a}$ (%) | 5.60 | 1.06 | 0.59 | 2.22 | 0.14 | -3.47 | -1.14 | -1.01 | -1.08 | -0.41 |
| | 5.97 | 1.59 | 0.78 | 1.70 | 0.10 | -2.81 | -1.32 | -1.83 | -2.46 | -1.74 |
| $\hat{d}$ | 0.26 | 0.14 | 0.02 | 0.12 | 0.13 | 0.50 | 0.20 | 0.19 | 0.20 | 0.06 |
| | 2.46 | 3.32 | 0.31 | 1.96 | 1.44 | 3.68 | 1.92 | 2.31 | 2.68 | 1.16 |
| $\hat{z}$ | -0.31 | -0.13 | -0.08 | -0.25 | -0.06 | 0.22 | 0.08 | 0.08 | 0.12 | 0.10 |
| | -5.37 | -2.75 | -1.25 | -2.14 | -0.48 | 2.12 | 0.96 | 1.45 | 2.21 | 2.02 |
| $Adj.\ R^2$ | 0.09 | 0.04 | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.01 | 0.02 | 0.01 |