The Development of Idiosyncratic Volatility: Evidence from the Dutch market

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Abstract

This paper examines aggregate idiosyncratic volatility in the Dutch equity market for the period from 1980 – 2009. The beta varying CAPM method as well as the model-independent method by Bali et al. (2008) has been used in order to calculate aggregate idiosyncratic volatility. This paper finds an overall upward trend in the unsystematic risk which is the result of a downward trend in the sample running until the early 1990’s and a larger upward trend until the end of the sample period. This time varying behavior is significantly different from earlier US market results. The upward trend in the Dutch idiosyncratic risk is mostly caused by firms in the financial industry. Furthermore the upward trend is stronger for firms that have a relatively low Market value, high Market-to-Book value, high Return on Equity, and/or high Earnings per share.

Keywords: Idiosyncratic volatility, trend test, diversification, portfolio selection, The Netherlands

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Chapter 1

Introduction

Asset pricing models such as the CAPM and the Fama-French three factor model ignore idiosyncratic risk and focus only on market risk due to diversification. However arbitrageurs, event studies, option pricing, and return risk in the case of under diversification are all affected by the idiosyncratic risk component. The time varying behavior of this component is therefore an interesting field of research.

Time variation in idiosyncratic volatility has been a growing point of focus for various researchers in the last decade. Campbell, Lettau, Malkiel and Xu (2001, hereafter CLMX) documented an increase in firm-specific risk in the US market by studying equities from 1962 until 1997. However Bekaert et al. (2010) and Brandt et al. (2010) show that extending the sample period results in a decrease in idiosyncratic volatility from 2000 onwards, which results in a concave pattern instead of an upward trend. With certainty can be said that the magnitude of idiosyncratic risk changes through time.

Since the findings of CLMX, much research has been done in order to identify determinants of the time varying behavior of idiosyncratic risk, being upward or concave. Many determinants have been identified including those focusing on the changing composition of stock market indices, corporate variables and behavioral issues. Although no consensus has been reached Bekaert et al. (2010) held a “comprehensive horserace” including numerous determinants and concluded that growth options, market to book value of assets and business cycle variables were most significant.

This paper investigates the time varying behavior of the Dutch equity market for the period from 1980 until 2009 using daily returns to construct monthly standard deviations. Residuals from the CAPM have been used to compose unsystematic risk for 121 stocks. The results are remarkable: the Dutch aggregate idiosyncratic volatility presents a convex function opposed to the recent results of the US market by Bekaert et al. (2010) and Brandt et al. (2010). Over the entire sample period the aggregate unsystematic risk follows an upward trend. Additionally the model-independent measure of aggregate idiosyncratic risk by Bali et al. (2008) has been used to compose an alternate sample of unsystematic volatility. This method yielded an upward trend as well, however the trend is of a weaker form. Differences between
both measures can be explained by the relatively small sample size which reduces the reliability of the Bali et al. (2008) method.

In order to verify the results trend tests have been performed to measure the existence of a trend and test for statistical significance; a robustness check has been performed by eliminating periods of distress and takeover rumors of dead equities; the sample has been split up to periods of economic expansions and economic downturns; and idiosyncratic risk has been aggregated using both equal and value weighting. These tests confirmed the results obtained through graphical analysis.

The CAPM results yet again provide many differences compared to earlier research. Although Europe has been investigated in bulk by Bekaert et al. (2010) and Kearney and Poti (2007) these results indicate that conducting research on other countries individually can result in a valuable contribution to the existing literature. As Brandt et al. (2010) point out in their research, these findings as well provide a challenge for the proposed determinants. In order for the already identified determinants to be applicable internationally they should be able to describe the time varying behavior of idiosyncratic risk in different countries. In this paper portfolios have been created based on the firms’ characteristics. The industry research shows that the Financial firms have had the largest influence on the upward trend in idiosyncratic risk. The fundamentals research indicates that idiosyncratic risk has a stronger upward trend for firms that have a low Market value, have a high Market-to-Book value, have high (or negative) Return on Equity, and/or have high (or negative) Earnings per share.

The rest of this paper is organized as follows. Chapter 2 provides a literature review on idiosyncratic risk and a summary of previous research on the existence of a trend of unsystematic risk and its determinants. Chapter 3 describes the composition of the data set used to measure aggregate idiosyncratic risk in The Netherlands. Chapter 4 describes the methodology used to calculate unsystematic risk. Chapter 5 contains the main results for this research. Chapter 6 summarizes the findings and also gives conclusions.
Chapter 2

Literature review

2.1 Idiosyncratic risk

2.1.1 Measuring idiosyncratic risk

The risk of a firm’s equity is denoted as the volatility of its returns and consists out of two elements. The first is the systematic or market risk which is associated with the market returns and the second element is the unsystematic or idiosyncratic risk which is firm-specific. Although the volatility of returns can be calculated rather easily using the standard deviation or variance, identifying the separate components is less straightforward. The idiosyncratic risk component is only indirectly observable by calculating the volatility of the residuals resulting from an asset pricing model. The most prominent model as we know it is the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965).

\[ R_{it} = R_{ft} + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it} \]  

(2.1)

With,

- \( R_{it} \) = The return for firm \( i \)
- \( R_{ft} \) = The risk-free rate
- \( R_{mt} \) = The market return

The asset’s variance can be decomposed using the Sharpe-Lintner CAPM equation (2.1):

\[ \sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_e^2 \]  

(2.2)

Under this expression the expected value of \( \sigma_e^2 \) (the idiosyncratic component of risk) and its covariance with the market’s return are assumed to be zero. The idiosyncratic risk is estimated relative to the systematic returns of securities and is therefore model dependent.\(^1\) The accuracy of the calculation of the idiosyncratic risk therefore depends on the accuracy of the market model. The CAPM is still widely used today and has been very influential on

\(^1\) Malkiel and Xu, 2003. *Investing the Behavior of Idiosyncratic Volatility*
financial literature. However the CAPM has not always been proved to be the most accurate asset pricing model. Although the unfamiliarity of the true market portfolio makes the CAPM not correctly testable,\(^2\) it has been tested extensively using proxies for the market portfolio. The results from these tests have not always been favorable for the CAPM\(^3\) and resulted in further research on asset pricing models such as the Fama-French three factor model.

Based on their research, Fama and French (1992) documented a relationship between a company’s size and its stock return. It appeared that smaller firms yield a higher return on average than large firms. Furthermore Fama and French find that firms with high book-to-market (BTM) ratios of equity (value stocks) have lower returns on average than presented by the CAPM. Firms with low BTM ratios (growth stocks) have higher returns on average. As a result of their findings, Fama and French (1993) presented their three-factor model containing (1) the excess return on a broad market portfolio, (2) the difference between the return on a small stock portfolio and a large stock portfolio, and (3) the difference between the return on a high BTM portfolio and a low BTM portfolio:

\[
R_{it} - R_{ft} = \beta_{im}(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_{HML} HML_t + \epsilon_{it} \tag{2.3}
\]

With,

\[
R_{it} - R_{ft} \quad \text{= The excess return for firm } i
\]

\[
\beta_i \quad \text{= The firm’s sensitivity to } (R_{mt} - R_{ft}), SMB_t \text{ and } HML_t
\]

\[
(R_{mt} - R_{ft}) \quad \text{= The excess market return}
\]

Fama and French (1996) find that the model is able to capture size, book-to-market and a long-term reversal effect. It is however not able to capture the short-term momentum effect. SMB in equation (2.3) stands for Small Minus Big and is computed as the average return of the smallest 30% of stocks minus the average return of the largest 30% of the stocks in that period. In the case that the SMB takes on a positive value means that on average small size stocks yield better results than large size stocks for that period. HML stands for High Minus Low and is computed as the average return of the highest 50% BTM stocks minus the average return of the lowest 50% BTM stocks. In the case that the HML takes on a positive value means that on average value stocks yield better results than growth stocks for that period.

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\(^2\) Roll, 1977. *A critique of the asset pricing theory’s tests, Part 1*

\(^3\) E.g. Black, et al., 1972; Merton, 1973; Fama and MacBeth, 1973
The third factor is the excess market return as forms the basis of the CAPM. In order to obtain expected excess return betas need to be regressed jointly on these three factors of the model.

**Figure 2.1:** Graphical presentation of SMB and HML

Where big represents stocks above the median market equity and small represents stocks below the median market equity. Low BTM stocks below the 30th percentile are situated on the left, those in the middle 40 percent are centered and the stocks in the top 30th percentile are situated on the right. Six value-weighted portfolios can be formed here.

Fama and French (1996) show that the three-factor model explains on average 93 percent of the variation in stock returns whereas the CAPM explains 78 percent on average. The Fama and French three-factor model therefore does a better job in explaining excess stock returns than the CAPM. Therefore the idiosyncratic component is also calculated more properly and is thus more reliable when obtained through the Fama-French model. However in this test a proxy for the true market portfolio has been used and therefore it cannot be said with absolute certainty that the Fama-French three factor model is in fact better.

2.1.2 A model-independent measure of aggregate idiosyncratic risk

Although a more sophisticated model like the Fama-French three factor model seems to explain the expected return of equities better than the CAPM, determining the idiosyncratic risk continues to be dependent of the model used. The correctness of the individual idiosyncratic risk component thus relies on the quality of the model. This however does not necessarily apply for the aggregate unsystematic risk in the market. The more recent work by
Bali et al. (2008) provides a measure of aggregate idiosyncratic risk which is model-independent. The method relies heavily on the concept of benefits of portfolio diversification as introduced by Markowitz (1952). The method calculates aggregate idiosyncratic risk as the difference in volatility between a well-diversified (contains only systematic risk) and a non-diversified portfolio (contains both systematic and unsystematic risk). The well-diversified portfolio is assumed to represent the market, which holds all securities whereas the non-diversified portfolio is constructed differently. The non-diversified portfolio does contain exactly the same assets, however the portfolios is calculated as if the assets are perfectly correlated ($\rho=1$) so no diversification gains are achieved. The variance of the non-diversified portfolio therefore is calculated as the weighted average of all variances in the portfolio thereby assuming that $\rho=1$. The main advantage of this method is the independence of asset pricing models which are still subject to many debates. Furthermore computational wise, this method requires less calculations. This method however has not yet been extensively tested for correctness and robustness by other researchers.

2.2 Idiosyncratic risk matters

The CAPM, the Fama-French three factor model and the method by Bali et al. (2008) all have in common that the models rely on the theory by Markowitz (1952) which explains the diversification effect. Through diversification the risk of investments can be reduced by eliminating idiosyncratic risk. Although idiosyncratic risk can be diversified away in a portfolio of stocks, there are several reasons to why, or situations in which firm-specific risk does matter. In this section these will be presented and discussed. The argumentation for conducting research in idiosyncratic risk thus lies within this section. The first paragraph will deal with firm-specific risk from an investor’s point of view in the light of diversification strategies presented in the previous section. The second paragraph discusses implications of idiosyncratic risk on arbitrageurs, event studies and option pricing. Lastly the (non)existence of predictive power of idiosyncratic risk will be discussed.

2.2.1 Diversification

The CAPM and the Fama-French three factor model assume that each investor is fully capable of eliminating all firm-specific risk in the portfolio by means of diversification.
However situations exist in which investors do not hold a well-diversified portfolio.\textsuperscript{4} Idiosyncratic risk is thus not or not completely eliminated and these investors should therefore incorporate total risk in their decisions and should not solely depend on market risk. This paragraph will first provide situations in which investors fail to diversify their portfolio, secondly discuss the issue of naïve diversification and finally the number of assets needed to fully eliminate the unsystematic risk will be discussed.

Listed companies often compensate their employees with stock option plans next to their fixed income. Employees who are not active in the investment in securities and receive stock option compensation are thus bound to one type of security. In this case the ‘investor’ clearly fails to diversify its holdings according to the standard models.\textsuperscript{5} French and Poterba (1991) found evidence for the existence of a home-bias of investors which implies that most investments in equities are allocated to domestic firms. Coval and Moskowitz, (1999), Grinblatt and Keloharju (2001), Huberman (2001) and Benartzi (2001) even found evidence for the presence of a home-bias within countries. Investors in this situation prefer investments in equities that are geographically close to their own homes. Barberis and Thaler (2003) explain evidence of home-bias from a behavioral point of view by means of ambiguity and familiarity. Investors may find stocks that are geographically close and/or within their own country more familiar than those further away. Familiar assets are more attractive and are therefore preferred as an investment. Coval and Moskowitz (2001) however also show that the home-bias can be an effect of superior information flows, especially in the case of mutual fund managers. It is less costly for these firms to research local firms and invest in those firms that have a higher expected return. Since the home-bias does not allow investors to diversify their portfolio holdings over the entire international market as predicted by standard theory, these investors may be insufficiently diversified. Baele et al. (2007) show however that when concerns of mistrust in the International CAPM are taken out, the degree of home-bias for many countries significantly decreases. Furthermore the degree of home-bias also decreases over time, mainly due to globalization and regional integration. Baele et al. (2007) however still recognize the existence of the home-bias.

One of the simplifying assumptions of the CAPM states that investments are limited to publicly traded assets and to risk-free borrowing and lending. Important other assets such as

\textsuperscript{4} Barberis and Thaler, 2003. \textit{A Survey of Behavioral Finance}

\textsuperscript{5} Campbell et al., 2001. \textit{Have Individual Stocks Become More Volatile?}
real estate, commodities, private equity and human capital are not included here whilst these assets can make up for a large part of a person’s wealth. Even when an investor strictly follows the CAPM he might not hold such a diversified holding after all. As an example, Baxter and Jermann (1997) therefore advise investors to “short assets on the national stock market because of its high correlation with their human capital.” This is remarkable since it is in conflict with the home-bias of investors.

The assumptions underlying the CAPM also neglect the existence of transaction costs. The amount of transaction costs rise however with the amount of stocks needed to diversify.\(^6\) Especially if diversification models indicate to invest in many small stocks (which are often perceived more profitable), the relative transaction costs are higher compared to large stocks.\(^7\) Because of this implication of transaction costs, an investor may choose not to fully diversify since at some point the incremental transaction costs can be larger than the incremental benefits of diversification.

Benartzi and Thaler (2001) find that when investors do decide to diversify they do so in a naïve way. The authors provide evidence that many investors use simple allocation strategies as allocating 1/n of their investable funds to each available investment. Benartzi and Thaler (2001) performed experiments by letting respondents make allocation decisions between stocks and bonds. Markowitz’ portfolio theory tells us to allocate funds to securities in such a way that for a desired level of expected return, the variance is minimized. The 1/n method will in most of the cases not result in an efficiently diversified portfolio.

Statman (1987) conducted research in the amount of stocks needed to efficiently diversify a portfolio. Before his paper was published conventional wisdom was that an investor would need 10 to 15 stocks to diversify the idiosyncratic risk. From Statman’s (1987) research however it appears that a well-diversified portfolio requires as a minimum 30 to 40 stocks. This requires (1) a larger amount of transaction costs due to the fixed transaction costs per stock and (2) may require more effort depending on the investment technique being used to determine the future expected return.

\(^6\) Campbell et al., 2001; Kearney and Poti, 2008; Malkiel and Xu, 2003
\(^7\) Falkenstein, 1996. Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings
Expected standard deviations of annual portfolio returns. With $n$ being the number of stocks in the portfolio and $\sigma$ being the standard deviation ($\%$).

As we can see in equations (2.4), the portfolio variance ($\sigma_P^2$) is determined by both the variances of the stocks and their correlations ($\rho_{ij}$).

$$\sigma_P^2 = w_A^2 \sigma_A^2 + w_B^2 \sigma_B^2 + 2w_A w_B \sigma_{AB}$$

With,

$W_i =$ Weight of asset $i$

$\sigma_i^2 =$ Variance of asset $i$

$\sigma_{ij} =$ Covariance of asset $i$ and $j$

Diversification is an effect of the correlation amongst the assets in the portfolio being smaller than one, and thus is an effect created on the right hand side of the equation. One can see that when the individual stock variances ($\sigma_i^2$) rise, $\sigma_P^2$ will go up as well. In portfolio management idiosyncratic risk thus matters since an aggregate rise in idiosyncratic risk will need to be compensated by a greater diversification effect in order to maintain the $\sigma_P^2$ at the desired level (this might not be even possible if an investor already holds a very well-diversified portfolio). The investor thus needs to add more stocks to the portfolio in order to create the desired

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8 Statman, 1987. *How Many Stocks Make a Diversified Portfolio?*
diversification effect in case aggregate unsystematic risk rises. As mentioned above, this can be a costly activity.

This paragraph has presented some cases and argumentation to why investors often do not hold a well-diversified portfolio. In these situations the CAPM does not hold for the investors since idiosyncratic risk is assumed to be zero. Investors should therefore also take the unsystematic risk (partly) into account in these situations.

2.2.2 Arbitrageurs, event studies and option pricing

In this paragraph other implications of idiosyncratic risks are presented in which this element is important to some actors.

Arbitrageurs who actively trade to benefit from mispriced individual securities in the market are exposed to risks that are more related to unsystematic risk instead of aggregate market risk.\(^9\) Larger pricing errors are possible when firm-specific risk is high however specialized arbitrageurs are not diversified and are therefore exposed to the idiosyncratic risk. Furthermore idiosyncratic risk cannot be hedged and as a result firm-specific risk therefore deters arbitrage.\(^10\)

Furthermore unsystematic volatility is important in event studies. In order to determine the statistical significance of abnormal event-related returns one must compare it relative to the market or industry.\(^11\)

Finally, under the Black and Scholes-Merton model the price of an option on an individual asset is dependent on the total volatility of the individual stock return, which includes both systematic and unsystematic risk.\(^12\) An increase in idiosyncratic risk (all else being equal) would have a negative effect on the value of the option.

2.2.3 Predictive power

This paragraph discusses the predictive power of average idiosyncratic risk on the return of the market as a whole. Goyal and Santa-Clara (2003) investigate the link between equity risk and returns in the stock markets. They find no evidence for the forecasting power of the

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\(^9\) Campbell et al., 2001. *Have Individual Stocks Become More Volatile?*

\(^10\) Shleifer and Vishny, 1997. *The Limits of Arbitrage*

\(^11\) Campbell et al., 2001. *Have Individual Stocks Become More Volatile?*

\(^12\) Titman and Martin, 2008. *Valuation*
lagged market variance for the market return which is consistent with several previous studies. They do however find a significant positive relation between the lagged average stock return variance and the return on the market. The stock return variance includes both systematic and unsystematic risk. Since the market risk did not have forecasting power over the market return, the unsystematic risk is held accountable for this significant positive relation. This result is in odds with financial economic models that rely on systematic risk instead on total risk. However because of the reasons provided in the previous paragraph it is not unthinkable that many investors hold non-diversified portfolios which could lead to this result. Similar results have been found by Guo and Savickas (2006, 2008) in the US and by Kearny and Poti (2008) in Europe.

Bali et al. (2005) however find that the relation as found by Goyal and Santa-Clara (2003) is mainly driven by the small stocks traded on the NASDAQ. Furthermore when the sample is extended the result also disappears. Moreover after using the value weighted approach to aggregate the results instead of the equal weighted approach the relation again is eliminated. This is partly a result of a liquidity premium.

2.3 Time variation in idiosyncratic risk

As described in the previous section, firm-specific risk can be quite important for investors. Idiosyncratic risk however is not constant and fluctuates over time. As we will see in the findings of the following paragraph, idiosyncratic risk tends to show large spikes during bubbles. According to several empirical studies the time varying behavior of idiosyncratic risk even shows a long term trend while this in turn is denied by more recent research. Irrespective of the existence of a trend, there is no consensus on what determines the time variation in firm-specific risk. This section first describes the preliminary research done by CLMX on idiosyncratic risk and subsequent related empirical work on time varying behavior of idiosyncratic risk. Secondly, empirical work on determinants of unsystematic risk will be discussed.

2.3.1 Trend in idiosyncratic risk

CLMX used a disaggregated approach to study the volatility in the returns of common stocks. Three levels were created to study different elements of volatility; being market, industry and

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13 Kearney and Poti, 2008. *Have European Stocks become More Volatile?*
firm level volatility. CLMX retrieved data from CRSP\textsuperscript{14} over the period from 1962 to 1997 from which they calculated realized monthly standard deviation using daily returns. Since CLMX used aggregated total volatility for their calculations without regarding the covariance terms they were able to avoid the estimation of beta coefficients. The results are presented in figure 2.3.

\textbf{Figure 2.3a: Market Variance}\textsuperscript{15}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{market_variance.png}
\caption{Market Variance}
\end{figure}

\textbf{Figure 2.3b: Industry Variance}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{industry_variance.png}
\caption{Industry Variance}
\end{figure}

\textsuperscript{14} CRSP: The Center for Research in Security Prices

\textsuperscript{15} Campbell et al., 2001. \textit{Have Individual Stocks Become More Volatile?}
Figure 2.3c: Firm Variance

Figure 2.3a shows the annualized variance within each month for daily returns of the market whereas figure 2.3b and 2.3c respectively show the industry annualized variance within each month for daily returns relative to the market and the firm annualized variance within each month for daily returns relative to the industry.

CLMX provide evidence by means of robustness checks and trend analyses that show a positive trend in firm volatility which is deterministic rather than stochastic. No similar result has been found for market or industry volatility. The absence of a trend in market volatility is consistent with Schwert (1989). However, an increase in aggregated firm-specific risk c.p. has a positive effect on market volatility. These results imply a decrease in correlations among individual stock returns. The increase in idiosyncratic risk has a positive effect on the number of stocks needed to achieve a certain degree of portfolio diversification.\(^\text{16}\) In the case that investors do not hold an optimal diversified portfolio the implications of an upward trend in idiosyncratic risk has a more direct effect due to the direct exposure to idiosyncratic risk. An upward trend in idiosyncratic risk thus has consequences for investors in these individual stocks.

The empirical research that followed CLMX was primarily focused on the US market. Kearney and Potì (2008) however examined the Euro Area with similar techniques. They also find an upward trend in idiosyncratic risk. Contradictory to CLMX they however also find a rise in market risk over time.

Bekaert et al. (2010) examined the aggregated unsystematic volatility in a very complete way. The authors researched the volatility in 23 developed markets (including US, Canada,

\(^{16}\) As has been discussed in paragraph 2.2.1
Australia, New Zealand, Japan, Hong Kong, Singapore and European countries), using various methods. Contradictory to the earlier results they however find no upward trend in the idiosyncratic volatility, in any of the 23 developed markets. They rather describe the evolvement of the firm-specific risk as “a stationary autoregressive process that occasionally switches into a higher-variance regime that has relatively short duration.” The trend thus exhibits spikes in certain periods. Brandt et al. (2010) find similar results for the US. It seems that lengthening the research period of CLMX’ sample results in a different conclusion. By 2003 idiosyncratic risk falls back to pre-1990’s levels, thereby not suggesting an upward trend. One can see that earlier research was limited by the availability of the data. By lengthening the dataset, idiosyncratic risk ones again drops and thus does not show an upward trend over the long run. This effect is clearly visible in figure 2.4.

**Figure 2.4a:** Idiosyncratic standard deviation from January 1926 to September 2008\(^\text{17}\)

The figure shows the annualized mean standard deviation (light line) and the 12-month backward moving average of this measure (dark line) for each month. Idiosyncratic volatility is measured using daily returns following the CLMX volatility decomposition methodology.

\(^{17}\)Brandt et al., 2010. *The Idiosyncratic Volatility Puzzle*
Figure 2.4b: Trend lines with one structural breakpoint

This figure shows the two trend lines when the aggregate idiosyncratic volatility time-series have a single breakpoint. The breakpoint is located in April 2000. The trend lines are fitted after computing the logarithm of idiosyncratic volatility. The annualized mean standard deviation (light line) for each month between January 1962 and September 2008. Idiosyncratic volatility is measured using daily returns following the CLMX volatility decomposition methodology.

Brandt et al. (2010) do not see the trend in idiosyncratic risk as completely stationary autoregressive with only occasional spikes. The authors do recognize an upward trend throughout the years, however interpret this as an episodic phenomenon because of its fallback to previous levels.

CLMX paved the way for further research in the development of idiosyncratic risk over time. It seems however that their conclusions were premature. The next paragraph will document the empirical analytical results in the search of determinants of unsystematic risk.

2.3.2 Determinants of idiosyncratic risk

CLMX did not empirically test for any determinants of the upward trend in idiosyncratic risk. They did however speculate that the upward trend may be a result from changes in corporate governance or the institutionalization of equity ownership. As influential factors concerning corporate governance CLMX primarily mention the tendency to break up conglomerates which creates more focused companies. These firms will continue to be listed separately and
replace the more diversified conglomerate. Secondly, the earlier issue of equity in firms’ lifecycles is pointed out as an explanatory factor. In this early stage of equity issuance profitability is not yet clearly established and the future prospects will be considered more uncertain. Thirdly CLMX point out the increase in risk taking that comes with executive stock option compensation. An increase in this form of compensation will have a positive effect on the volatility of the firms’ returns.

There has been an increase in the share of institutional ownership and particularly for large stocks. The institutional investors may be influenced by a few common factors because of the small group they form. Shocks to the sentiment of this group of investors are possibly related to idiosyncratic risk. An increase in institutional ownership may drive up the idiosyncratic risk since only a small group of investors control a larger share in stocks.

Bekaert et al. (2010) classify the identified determinants into three groups being (1) the changing composition of stock market indices, (2) the firm-specific characteristics that ultimately determine idiosyncratic cash flow variability (corporate variables), and (3) behavioral issues that affect market inefficiencies. This paragraph presents the most important findings in these groups of determinants.

The number of firms that obtain public equity through the US stock market changes dramatically in the 1980’s and 1990’s. The number of new listed firms on the US stock exchanges jumps from 156 per year (1973-1979) to 549 per year (1980-2001). These firms are characterized by less profitability and more growth. The new lists are thus riskier and this negatively affects the survival rates of new lists in general.¹⁸ Pástor and Veronesi (2003) show that firm profitability has become more volatile which positively influences the idiosyncratic risk of individual firms. The authors ascribe this effect to the new listings. Fink et al. (2005) find that the recent rise in idiosyncratic risk is driven by the increasing propensity of firms to issue public equity at an earlier stage in their life cycle when they are riskier. Brown and Kapadia (2007) find that the rise in idiosyncratic risk is indeed caused by more risky firms that become listed. These firms however are not necessarily smaller but are part of a riskier sub-sample of the economy.

The second set of articles includes those that focus on corporate variables as determinants. These corporate variables are company-specific characteristics that will determine the cash

---

flow variability which will ultimately lead idiosyncratic risk. Wei and Zhang (2006) explained the upward trend in idiosyncratic risk by means of corporate earnings. From a fundamentalist point of view, the present value of a company is to be deducted from the discount value of all future dividends. Wei and Zhang (2006) however argue that dividends are often smoothed and are therefore not useful as an independent variable. The authors believe that earnings therefore reflect more information about future profitability of the firm and are subject to a lesser form of manipulation. In their article Wei and Zhang (2006) show that the idiosyncratic trend is explained by a downward trend in return-on-equity and an upward trend in the volatility of the return-on-equity. They do however acknowledge that most of this effect is caused by newly listed stocks as was the result of the first set of articles. Cao et al. (2007) show that the increase in idiosyncratic risk is an effect of both the level and variance of corporate growth options. For levered firms the moral hazard exists that managers, who are acting on behalf of the shareholders, choose those projects that increase the unsystematic volatility at the expense of the debt holders. Comin and Philippon (2005), Gaspar and Massa (2005) and Irvine and Pontiff (2008) find evidence that an increase in economy wide product competition drives up the firm-specific risk. Having a substantial amount of market power can work as a natural hedge that smoothes out cash flow fluctuations that result from unsystematic cost shocks. Furthermore a firm with monopoly power can shift larger portions of idiosyncratic cost shocks to its customers, whereas a company in a highly competitive industry would have a harder time in doing this. Having market power also takes away a portion of uncertainty about the company’s future results. Higher competition thus creates more uncertainty towards investors. The upward trend in idiosyncratic risk is also ascribed to the (lack of) opaqueness, accounting standards and investor right protection by another sub-set of papers.19 “Improving disclosures and the quality of financial reporting mitigates information asymmetries about a firm’s performance and reduces the volatility of stock prices.”20 Similarly improved investor right protection also mitigates information asymmetry. Worsening standards however will have a positive effect on the idiosyncratic volatility. Comin and Philippon (2005) and Chun et al. (2008) also link the trend to an increase in R&D spending. Waves of radical innovations, combined with deregulation and lowering the barriers of trade may result in more intense competition and creative destruction. The

19 Jin and Meyers, 2006; Chun et al., 2008; Rajgopal and Venkatachalam, 2008
20 Rajgopal and Venkatachalam, 2008. Financial Reporting Quality and Idiosyncratic Return Volatility over the Last Four Decades
instability of these businesses leads to an increase in idiosyncratic risk.\textsuperscript{21} This theory does not necessarily rule out the hypotheses of smaller or younger and riskier firms listing on the exchange. Neither does it coincide with the hypothesis of intensified competition. Comin and Philippon (2005) argue that R&D spending is an effect of intensified competition since there is a trade-off between R&D and general innovations. General innovations are hard to patent and therefore benefit both the innovator and the market whereas R&D innovations are patentable and benefit the innovator mostly. Individual companies are therefore trying to differentiate themselves which lowers correlation among companies and increases the unsystematic risk.

The third group of articles belongs to behavioral variables that influence idiosyncratic risk. Bennet et al. (2003) and Xu and Malkiel (2003) argue that an increase in institutional ownership is associated with an upward trend in unsystematic risk. In the case of institutional ownership selling and buying is more likely to be coordinated across institutions, which may cause stock prices to become more volatile and more responsive to market changes and information flows. Brandt et al. (2010) and Foucault et al. (2009) however ascribe episodic shifts in unsystematic risk to speculative behavior. They argue that retail trading has gone up because barriers to trading have gone down. Retail trading makes up for a large part of idiosyncratic risk. Brandt et al. (2010) explain that the 1990’s episode of high idiosyncratic risk was primarily a result of firms with low stock prices and limited institutional ownership.

The determinants presented above (except for the findings by Brandt et al.) were tested on aggregate idiosyncratic risk that was trended upward. Bekaert et al. (2010) and Brandt et al. (2010) however argue that there is no upward trend in unsystematic risk. This does not mean that earlier findings on determinants are obsolete. Next to the upward moving behavior, these determinants however should also show a sudden drop over the past few years. Based on their findings, Brandt et al. (2010) conclude that retail trading has the best link with the trend in unsystematic risk. Bekaert et al. (2010) however ran a “comprehensive horse race” using the variables as researched in earlier work (cash flow variables) and added business cycle variables as well as market wide variability. The business cycle variables are introduced to test for relations with recessions and discount rate volatility. The authors find that all three classes of variables, cash flow, business and market wide volatility, are

\textsuperscript{21} Chun et al., 2008. Creative destruction and firm-specific performance heterogeneity
important determinants of the time variation in US aggregate unsystematic risk. Growth options and market to book value of assets were most significant as cash flow variables, whereas the variance premium\textsuperscript{22} was the most important variable in the business cycle class. Bekaaert et al. (2010) do however seriously question the use of linear models to explain the trend in idiosyncratic volatility.

Although it is unknown how the idiosyncratic risk will evolve in the future, it has to be concluded on the basis of the latest data that an upward trend in idiosyncratic risk does not exist. However the data does exhibit an episodic event in which unsystematic risk initially increases and finally decreases relatively fast. Although a lot of research on determinants has been conducted we cannot give a robust conclusion on the question to what drives the idiosyncratic risk.

\textsuperscript{22} The difference between the square of the VIX index, an option based measure of the expected variability in the stock market, and the actual physical variance of the stock returns
<table>
<thead>
<tr>
<th>Authors</th>
<th>What was examined (Time period)</th>
<th>Method</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Campbell et al. (2001)</td>
<td>Stock volatility from US NYSE/AMEX/Nasdaq from CRSP (1962 - 1997)</td>
<td>Disaggregated approach of the CAPM model in which no regression of betas is necessary</td>
<td>A noticeable increase in firm-level volatility relative to market volatility. Correlations among individual stocks have declined.</td>
</tr>
<tr>
<td>Fink et al. (2005)</td>
<td>Determinants of idiosyncratic risk of US stocks from CRSP and Compustat (1925 - 1997)</td>
<td>CLMX</td>
<td>An upward trend in idiosyncratic risk, positively related to the increasing propensity of firms to issue public equity at an earlier stage in their life cycle</td>
</tr>
<tr>
<td>Comin &amp; Philippon (2005)</td>
<td>Determinants of idiosyncratic risk of US stocks from CRSP and Compustat (1926 - 2004)</td>
<td>CAPM with varying betas</td>
<td>An upward trend in idiosyncratic risk, positively related to the increase of competition which in turn is caused by increases in R&amp;D investments and more debt issuance</td>
</tr>
<tr>
<td>Bekaert et al. (2010)</td>
<td>Determinants of idiosyncratic risk of stocks from 23 developed countries from CRSP, Datastream and Compustat (1964/1980 - 2008)</td>
<td>CLMX</td>
<td>No upward trend in idiosyncratic risk but instead a stationary autoregressive process that occasionally switches to a higher-variance regime. Growth opportunities, market volatility and the variance premium determine the variation</td>
</tr>
</tbody>
</table>
2.4 The Dutch market

Kearney and Poti (2008) chose to investigate the idiosyncratic risk in the Euro zone as a whole. They argue that the European equity markets have integrated more and more since the mid-1990’s. Moreover, the introduction of the Euro as a currency, increased correlations amongst countries. Ferreira and Ferreira (2006) however find that national effects are still important drivers of individual stock returns in the Euro area. It is therefore important to also investigate these countries separately.

This paper will research the existence of a trend in idiosyncratic volatility on the Dutch market. The Dutch stock indices are listed by the equities exchange group NYSE Euronext. The national stocks are listed in Amsterdam on primarily three indices, the Amsterdam Exchange Index (AEX), the Amsterdam Midcap Index (AMX), and the Amsterdam Small cap Index (AScX). The AEX consists out of the 25 largest and most traded stocks over the previous calendar year, the AMX out of the next 25 stocks and the AScX contains the third set of 25 stocks. 23

In the next chapter the process of data selection of the securities listed on the Amsterdam exchange will be discussed.

Chapter 3

Data selection

3.1 Data collection

This paper assesses the time varying behavior of aggregate idiosyncratic risk in The Dutch stock market during the period 1980 – 2009. Daily stock prices and market values that will make up the sample have been retrieved from Thomason Financial DATASTREAM (DataStream). The data contains all equities on the Euronext Amsterdam listing during the sample period, both active and inactive and amount to 589 stocks over more than 7,800 trading days. For each trading day returns have been calculated from the stock prices. In order to calculate CAPM returns the risk-free rate is also needed in order to calculate excess returns. Since the risk-free rate is the return on a risk-free investment it is necessary to choose a product that is close to having no default risk. The German short-term interest rate has been retrieved from DataStream to represent the risk-free rate as Germany has proved to be an economically stable country in Europe throughout history.

3.2 Sample construction

In order to obtain reliable results for this research it is of importance to have consistent data. The data has to be adjusted for errors and certain requirements have to be made in order to obtain a reliable sample. Therefore five steps are executed:

1. The first change in the sample is an effect of errors in DataStream. For several stocks data is not available in DataStream and therefore has to be eliminated from the sample resulting in a sample size of 454 equities;

2. The sample needs to be corrected for size since small companies may suffer from infrequent trading and low volumes. This may lead to inefficient pricing and therefore need to be eliminated from the sample. Bekaert et al. (2009) used a minimum market value of $1 million for their international study of stock return comovements. However since the Dutch market is not the largest one of its kind when looking at market values
internationally, a minimum of €500,000 will be required. The minimal market value has to be achieved for a minimum of 500 trading days;

3. The requirement of a minimum market value of €500,000 for a minimum of 500 trading days covers a second requirement. Stocks with less than 500 observations need to be eliminated from the sample since these may also suffer from pricing errors because of their short lived presence. The combined measure therefore results in a sample size of 134;

4. Stocks that are listed but are not subject to trading will not contribute to a reliable sample for the research purposes at hand. Non-traded stocks are not followed by the market and possibly not correctly priced. Therefore stocks with zero return over more than 500 trading days are eliminated from the sample resulting in a sample size of 121;

5. The sample is divided in a dead and active sample in order to be able to perform robustness checks in a later phase of the research.

The final sample size of individual stocks amounts to 121. Next to the individual stock returns and the risk-free rate, the market return is needed as well in order to calculate idiosyncratic risk by means of an asset pricing model. Since the true market portfolio is hard to determine, two alternatives will be used. Primarily a value weighted market index will be created from the securities in the data sample and secondly a global market index (series code: TOTMKWD) is obtained from DataStream. The correlation between both market portfolios is 0.65. In Table 3.1 descriptive statistics for the sample of equities are displayed. In the next chapter the research methodology will be discussed.
Table 3.1: Descriptive statistics for the Dutch sample:

<table>
<thead>
<tr>
<th>Equities</th>
<th>N</th>
<th>Mean</th>
<th>Std. dev</th>
<th>MIN</th>
<th>MAX</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1980 - 2009</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active</td>
<td>58</td>
<td>0.0657%</td>
<td>2.4831%</td>
<td>-72.41%</td>
<td>102.70%</td>
</tr>
<tr>
<td>Dead</td>
<td>63</td>
<td>0.0713%</td>
<td>2.2079%</td>
<td>-95.77%</td>
<td>221.45%</td>
</tr>
<tr>
<td>All</td>
<td>121</td>
<td>0.0682%</td>
<td>2.3629%</td>
<td>-95.77%</td>
<td>221.45%</td>
</tr>
<tr>
<td><strong>1980 - 1989</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active</td>
<td>32</td>
<td>0.0886%</td>
<td>1.9831%</td>
<td>-40.79%</td>
<td>63.21%</td>
</tr>
<tr>
<td>Dead</td>
<td>44</td>
<td>0.0934%</td>
<td>2.0329%</td>
<td>-41.31%</td>
<td>60.91%</td>
</tr>
<tr>
<td>All</td>
<td>76</td>
<td>0.0914%</td>
<td>2.0128%</td>
<td>-41.31%</td>
<td>63.21%</td>
</tr>
<tr>
<td><strong>1990 - 1999</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active</td>
<td>53</td>
<td>0.0785%</td>
<td>1.7924%</td>
<td>-35.87%</td>
<td>38.63%</td>
</tr>
<tr>
<td>Dead</td>
<td>58</td>
<td>0.0657%</td>
<td>1.8093%</td>
<td>-51.02%</td>
<td>58.33%</td>
</tr>
<tr>
<td>All</td>
<td>111</td>
<td>0.0720%</td>
<td>1.8009%</td>
<td>-51.02%</td>
<td>58.33%</td>
</tr>
<tr>
<td><strong>2000 - 2009</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active</td>
<td>58</td>
<td>0.0457%</td>
<td>3.0639%</td>
<td>-72.41%</td>
<td>102.70%</td>
</tr>
<tr>
<td>Dead</td>
<td>46</td>
<td>0.0441%</td>
<td>3.0331%</td>
<td>-95.77%</td>
<td>221.45%</td>
</tr>
<tr>
<td>All</td>
<td>104</td>
<td>0.0452%</td>
<td>3.0552%</td>
<td>-95.77%</td>
<td>221.45%</td>
</tr>
</tbody>
</table>

The table contains the mean, standard deviation, minimum and maximum (in percentages) of the daily returns for the sample. The results are displayed separately for active and dead stocks and listed per period.
Chapter 4
Methodology

This paper measures aggregate idiosyncratic volatility using two different approaches. Primarily the CAPM will be used and secondly the model-independent method of Bali et al. (2008) will serve as a measure of aggregate unsystematic risk.

4.1 CAPM measure of idiosyncratic volatility

CLMX use a disaggregated approach to study the idiosyncratic volatility. This method decomposes the excess return on an individual stock into three components; a market wide return, an industry-specific residual and a firm-specific residual. The decomposition assumes that the different components of a firm’s return are orthogonal to one another and assume beta unity. Hence permits a simpler variance decomposition in which the covariance terms are zero and can therefore be neglected. Therefore CLMX avoid the estimation of industry or firm-level beta coefficients. The intuition behind this method lies in the unreliability of using a constant-beta market model. They do however impose unit beta restrictions. Using a constant-beta market model and assuming market betas to be equal to one “may lead to serious biases in measures of country and industry diversification potential.” Baele and Inghelbrecht (2009) indicate that market betas differ and vary through time since (1) increased market integration leads to an increase in global factor exposures, (2) industry betas vary over time due to changes in regulations and industry characteristics and (3) even without structural changes, betas can vary over time because of business cyclicality. Furthermore Bekaert et al. (2009) argue that the beta restrictions as in CLMX’ approach severely limit the model’s ability to match stock return comovements.

This paper therefore does not follow the method as described by CLMX. The CAPM model will be used to calculate idiosyncratic risk however betas will be estimated and will vary over time. The equity returns as described in the previous chapter are used to create a value weighted index to serve as a proxy for the market portfolio:

24 Wei and Zhang, 2006. Why Did Individual Stocks Become More Volatile?
25 Baele and Inghelbrecht, 2009. Time-varying Integration and International diversification strategies
With,

\[ R_{i,m} = \text{The return to shareholders of firm } i \text{ in day } m \text{ of year } t \]
\[ R^M_{t,m} = \text{The daily return on the value weighted index (market) in day } m \text{ of year } t \]
\[ W_{i,t-1,m} = \text{The market value weight of firm } i \text{ in day } m \text{ of year } t-1 \]

The weights are derived from the market value of the firm per day. The risk-free rate is deducted from the individual and market returns in order to calculate the excess returns \( r_{i,m} \) and \( r^M_{t,m} \). Similarly the excess returns will be calculated for the global market index, the alternative proxy for the market portfolio.

For each individual firm market betas will be estimated and re-estimated for every subsequent month using the equation in figure 4.1. The beta for each month \( m \) will be calculated on the basis of the standard deviation and covariance of month \( m-5 \) up until including month \( m \). Hence each stock in the sample will have a beta for the global market index and the value weighted index for each month it has returns.

**Figure 4.1: Beta calculation**

\[ \beta_i = \frac{\text{Cov}(R_i, R^M_t)}{\sigma^2(R^M_t)} \]

Figure 4.1 graphically presents the calculation of the betas for each subsequent month.

Subsequently the CAPM model will be used to calculate expected excess return for each day in the sample:

\[ r_{i,t,m} = \beta_{i,t} R^M_{t,m} + \varepsilon_{i,t,m} \]  

With,

\[ \beta_{i,t} = \text{The beta for stock } i \text{ and } R^M_{t,m} \text{ in year } t \]
\[ \varepsilon_{i,t,m} = \text{The idiosyncratic return component of stock } i \text{ in day } t \]
The error term is expected to be zero in calculating the CAPM expected returns. Subtracting the CAPM expected excess return from the realized excess return will yield the residual from the model which is thus firm-specific. As explained in paragraph 2.1.1, the volatility of this residual represents the idiosyncratic risk. We will therefore calculate monthly standard deviations of daily residuals for each individual firm. The aggregate idiosyncratic standard deviation will be calculated using value weighting:

$$\sigma_{izz,n} = \sum_{i=1}^{n} W_{i,t-1,n} \sigma_{i,izz,n}$$  (4.3)

With,

$$\sigma_{izz,n} = \text{The aggregate idiosyncratic standard deviation in month } n \text{ of year } t$$

$$\sigma_{i,izz,n} = \text{The idiosyncratic standard deviation of firm } i \text{ in month } n \text{ of year } t$$

$$W_{i,t-1,n} = \text{The market value weight of firm } i \text{ in month } n \text{ of year } t-1$$

Additionally the aggregate idiosyncratic volatility will be calculated using equal weighting.

### 4.2 Model-independent measure of idiosyncratic volatility

As has been discussed in paragraph 2.1.2 the model-independent measure of idiosyncratic volatility has the advantage to outstrip the asset pricing model discussion as it relies primarily on Markowitz’ (1952) theory of diversification benefits. The daily excess return of the value weighted index \( \tau_{iz,m} \) as created for the CAPM method will serve as the well-diversified portfolio as it represents the Dutch equity market. The non-diversified portfolio will be created using the weighted average of all firms as well however correlations will be assumed to be equal to one. The standard deviation of the non-diversified portfolio therefore becomes:

$$\sigma_{p,n} = \sum_{i=1}^{n} W_{i,t-1,n} \sigma_{i,n}$$  (4.4)

With,

$$\sigma_{p,n} = \text{Standard deviation of returns of the non-diversified portfolio in month } n \text{ of year } t$$
\[ \sigma_{i.t.n} = \text{Standard deviation of daily returns of firm } i \text{ in month } n \text{ of year } t \]

The benefits of diversification, or the elimination of the idiosyncratic risk, can be calculated by subtracting the well-diversified portfolio standard deviation from the non-diversified portfolio standard deviation:

\[ \sigma_{A.t.n} = \sigma_{p.t.n} - \sigma_{M.t.n} \quad (4.5) \]

With,

- \( \sigma_{A.t.n} \) = The aggregate idiosyncratic standard deviation in month \( n \) of year \( t \)
- \( \sigma_{p.t.n} \) = Standard deviation of returns of the non-diversified portfolio in month \( n \) of year \( t \)
- \( \sigma_{M.t.n} \) = Standard deviation of daily market returns in month \( n \) of year \( t \)

Bali et al. (2008) found significant difference between the results of their new method and the CLMX method. The time varying behavior however was quite similar to the CLMX method.

The next chapter will show the results based on the methodology as described in this chapter. Furthermore the data will be tested for the existence of a trend as has been the discussion in the literature.
Chapter 5

Results

5.1 Graphical analysis and descriptive statistics

The results of the computation of the aggregate idiosyncratic risk in the Dutch market are graphically presented in this section (figure 5.1). The results have been displayed for the different methods used as has been described in the previous chapter. Furthermore in table 5.1 descriptive statistics can be found of the results of the different measurement methods.

Table 5.1: Descriptive statistics of aggregate idiosyncratic risk

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean * 10^2</th>
<th>Std. dev. * 10^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bali et al. (2008)</td>
<td>7.244</td>
<td>0.944</td>
</tr>
<tr>
<td>CAPM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Market Index</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td>13.633</td>
<td>2.050</td>
</tr>
<tr>
<td>Equal Weighting</td>
<td>13.393</td>
<td>2.036</td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td>16.472</td>
<td>2.328</td>
</tr>
<tr>
<td>Equal Weighting</td>
<td>15.807</td>
<td>2.187</td>
</tr>
</tbody>
</table>

This table reports basic descriptive statistics (annualized mean and annualized standard deviation) from the Dutch aggregate idiosyncratic model for each method used.

Table 5.1 shows quite some varying levels of annualized means and standard deviations of idiosyncratic risk. The differences in these levels due to the measurement method however will be discussed in paragraph 5.2.3. Interesting here is to compare the levels of average idiosyncratic risk with earlier research which has been summarized in table 5.2. Unfortunately there has not been conducted much research on the Dutch idiosyncratic volatility. Bekaert et al. (2010) found levels of 17.088 and 19.209 for the Dutch market being the only measure of comparison. These are slightly higher than the CAPM value weighted index results from this sample and quite high compared to the global market index results. Compared to the Bali et al. (2008) results they are far greater. Other levels of idiosyncratic risk of earlier research are based on the US market. It can be seen from the study by Bekaert...
et al. (2010) that the US level of idiosyncratic risk is substantially higher than the Dutch unsystematic risk. The CLMX method yields a 66% higher annualized mean of idiosyncratic standard deviation for the US market whereas the Fama – French method yields a 37% higher level. The results by Bekaert et al. (2010) are quite high compared to Brandt et al. (2010) and CLMX and therefore the levels resulting from this research seem to be around the expected levels and possibly slightly on the low end.

**Table 5.2:** Aggregate idiosyncratic risk levels of earlier research

<table>
<thead>
<tr>
<th>Authors / Method</th>
<th>Mean * 10²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bekaert et al. 2010</strong></td>
<td></td>
</tr>
<tr>
<td>1980 - 2008 Netherlands</td>
<td></td>
</tr>
<tr>
<td>CLMX</td>
<td>17.088</td>
</tr>
<tr>
<td>Fama - French</td>
<td>19.209</td>
</tr>
<tr>
<td>1964 - 2008 US</td>
<td></td>
</tr>
<tr>
<td>CLMX</td>
<td>28.284</td>
</tr>
<tr>
<td>Fama - French</td>
<td>26.401</td>
</tr>
<tr>
<td><strong>Brandt et al. 2010</strong></td>
<td></td>
</tr>
<tr>
<td>1980 - 2008 US</td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td>8.789</td>
</tr>
<tr>
<td>Equal Weighting</td>
<td>18.811</td>
</tr>
<tr>
<td><strong>Campbell et al. 2001</strong></td>
<td></td>
</tr>
<tr>
<td>1962 - 1997 US</td>
<td></td>
</tr>
<tr>
<td>Raw data</td>
<td>25.375</td>
</tr>
<tr>
<td>Downweighted Crash</td>
<td>25.265</td>
</tr>
</tbody>
</table>

This table reports the annualized means of aggregate idiosyncratic standard deviation of earlier research. Stated are the time period, investigated market and method used.
**Figure 5.1a:** Aggregate idiosyncratic risk: CAPM Global Market Index

This figure shows the monthly aggregate idiosyncratic standard deviation for the Dutch market for the period June 1980 – December 2009 based on daily returns. The CAPM has been used to compute residuals for which the global market index (TOTMKWD) served as a proxy for the market portfolio. Standard deviations have been aggregated using value weighting (VW) and equal weighting (EW).

**Figure 5.1b:** Aggregate idiosyncratic risk: CAPM Value Weighted Index

This figure shows the monthly aggregate idiosyncratic standard deviation for the Dutch market for the period June 1980 – December 2009 based on daily returns. The CAPM has been used to compute residuals for which the value weighted market portfolio of the assets in the sample served as a proxy for the market portfolio. Standard deviations have been aggregated using value weighting (VW) and equal weighting (EW).
This figure shows the monthly aggregate idiosyncratic standard deviation for the Dutch market for the period January 1980 – December 2009 based on daily returns. The model-independent method by Bali et al. (2008) has been used to calculate the aggregate idiosyncratic volatility.

Based on the graphs, the CAPM results show a quite similar pattern of larger spikes as has been the result for the US market by Bekaert et al. (2010) and Brandt et al. (2010). We can see similar occasional higher regimes of idiosyncratic risk during recessions for both markets however the Dutch spikes are not quite as extreme, especially during the time of the dot-com bubble. It is difficult to give a conclusion of a trend based solely on figure 5.1. However based on the CAPM results it seems that the aggregate idiosyncratic risk drops from the start of the sample until approximately 1992 (stronger for the Value Weighted Index results) and subsequently rises upward.

This observation of convexity in these results is fundamentally different from the observations in the US market by Bekaert et al. (2010) and Brandt et al. (2010) where the time-series display functions which in essence are concave. The idiosyncratic risk as measured by the model-independent measure by Bali et al. (2008) does not immediately indicate the existence of a trend.

According to Brandt et al. (2010) the US volatility falls back to pre-1990 levels in 2003. The fall in 2003 however is not as deep for the Dutch market as it was for the US.

See Figure 2.4b
Since the sample also contains dead securities, the aggregate unsystematic risk could be affected by periods of uncertainty due to takeovers or distress. Therefore an additional robustness check has been performed to verify the results for which this effect has been eliminated. The returns in the last month before elimination of the stocks in the dead sample have been deleted to control for this uncertainty. The differences in aggregate idiosyncratic risk however are negligible and therefore not presented here.

The next section will perform trend tests in order to provide a measure to determine whether a trend exists in the aggregate firm-specific risk in the Dutch equity market.

5.2 Measuring trends

5.2.1 Total period

This paragraph will test for the existence of a trend based on the total sample period by means of linear regression. This research focuses on the long-term time varying behavior of idiosyncratic risk and therefore the total period is of most importance, even though it seemed that different periods exhibit different trends, based on the graphical analysis. When time-series contain structural breaks – which could be the fact based on the previous section - trend test results could be disturbed. It would be preferable to perform a trend test using the PS statistic by Vogelsang (1998). This method has been frequently used in earlier research on aggregate idiosyncratic risk.²⁷ Vogelsang’s (1998) technique is also preferred in case the data is subject to high persistence. Although the method is recognized in this section to be preferred over others it will not be used because of its complexity.

In order to test for a trend in the sample data linear trend regressions have been performed. The results can be found in table 5.3 for the different methods used. The first panel shows the results of the “raw data” that are not subject to any adjustments. Over the entire sample period the beta coefficients are positive for all measurement methods indicating an upward trend. The coefficient for the model-independent method as proposed by Bali et al. (2008) is rather small compared to the CAPM results however statistically significant at the 1% level.

²⁷ E.g. Bekaert et al., 2010; Brandt et al., 2010; Campbell et al., 2001
The CAPM results are significantly larger in size and as well statistically significant at the 1% level.

The second panel exhibits results for the sample data during periods of economic expansions. Periods of economic expansions are identified by the Composite Leading Indicator (CLI) time-series from the OECD. These aggregated time-series, which have a long-term average of 100, have been composed of a set of components that have been selected from a range of key short-term economic indicators. Turning points in the economy of a country or region can be identified by the CLI. The period between a periodic minimum (through) and a periodic maximum (peak) indicates expansion whereas a period between a peak and a through indicates a recession. The third panel represents similar data however based on the sample during periods of economic downturns. It becomes clear from this data that aggregate idiosyncratic risk is higher during economic downturns, as well as being more volatile. Furthermore during the economic downturns the beta representing the upward trend over time is significantly larger. Another important observation can be derived here; even during economic expansions, the aggregate idiosyncratic risk still exhibits a statistically significant upward trend over time.

Table 5.3: Descriptive statistics and trend regression results for raw sample data and sample data down weighted for economic downturns

<table>
<thead>
<tr>
<th>Method</th>
<th>Raw data</th>
<th>Economic Expansions</th>
<th>Economic Downturns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. dev.</td>
<td>Beta</td>
</tr>
<tr>
<td></td>
<td>$10^2$</td>
<td>$10^2$</td>
<td>$10^5$</td>
</tr>
<tr>
<td>Bali et al. (2008)</td>
<td>7.244</td>
<td>0.944</td>
<td>0.860***</td>
</tr>
<tr>
<td>CAPM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Market Index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equal Weighting</td>
<td>13.393</td>
<td>2.036</td>
<td>3.434***</td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td>16.472</td>
<td>2.328</td>
<td>1.866***</td>
</tr>
</tbody>
</table>

This table presents basic descriptive statistics (annualized mean and annualized standard deviation) and trend regression beta coefficients from the Dutch aggregate idiosyncratic standard deviation for each method used. Three panels have been created; the first containing raw sample data, the second panel presenting results from the sample during economic expansions and the third presenting results for the sample during economic downturns. The significance of the coefficients is indicated by the number of asterisks:

* Statistically significant at the 10% level
Figure 5.2: Composite Leading Indicator (CLI) time-series for The Netherlands

This figure presents the time-series of the Composite Leading Indicator (CLI) created by the OECD for The Netherlands. CLI is constructed by aggregating together component series selected according to multiple criteria, such as: economic significance, cyclical correspondence and data quality. The time-series indicate turning points in the state of the economy. The period between a trough (periodic minimum) and a peak (periodic maximum) represents expansion whereas the period between a peak and a trough represents recession.

These regression results however may be inaccurate if the data turns out to be non-stationary. The use of non-stationary data can lead to spurious regressions. Furthermore the standard assumptions for asymptotic analysis will not be valid when using non-stationary data. Hence the $t$-ratios used in table 5.3 to test the statistically significance would not follow the $t$-distribution and could thus be interpreted incorrectly. One way to test the data for stationarity is to test the data on the presence of unit roots. With stationary data an unexpected change in the data (or shock) will gradually die away and will not have a systematic effect on the proceeds of the data. For non-stationary data the effect of a shock will be persistent and will not die away, hence contains a unit root.

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Brooks, 2008. Introductory Econometrics for Finance
In order to test for unit roots the Augmented Dickey-Fuller unit root test has been used. The use of the traditional Dickey-Fuller unit root test\textsuperscript{30} would have implied that the white noise \((u_t)\) in the data is not autocorrelated. The existence of autocorrelation in the data could lead to an oversized test using this model and could incorrectly reject the null hypothesis. It is therefore that this paper uses the Augmented Dickey-Fuller unit root test which “soaks up any dynamic structure present in the dependent variable, to ensure that \(u_t\) is not autocorrelated.”\textsuperscript{31} Table 5.4 contains the results of these tests for the different methods used to compose the aggregate idiosyncratic risk of the raw data.

**Table 5.4: Augmented Dickey-Fuller Unit root tests results**

<table>
<thead>
<tr>
<th>Method</th>
<th>Raw data</th>
<th>Intercept Coefficient</th>
<th>Intercept &amp; Trend Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bali et al. (2008)</td>
<td></td>
<td>-0.4078***</td>
<td>-0.4747***</td>
</tr>
<tr>
<td>CAPM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Market Index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td></td>
<td>-0.1375***</td>
<td>-0.1821***</td>
</tr>
<tr>
<td>Equal Weighting</td>
<td></td>
<td>-0.0940**</td>
<td>-0.1843***</td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighting</td>
<td></td>
<td>-0.1475***</td>
<td>-0.2151***</td>
</tr>
<tr>
<td>Equal Weighting</td>
<td></td>
<td>-0.1642***</td>
<td>-0.2022***</td>
</tr>
</tbody>
</table>

This table contains the coefficients for the Augmented Dickey-Fuller Unit root tests for the different methods used to create the time-series. Results are displayed for tests including an intercept and for the tests including an intercept and a trend. The lag length has been automatically selected using the Schwarz Criterion with a maximum amount of lags of 16. The asterisks indicate the level of statistical significance that the null hypothesis, time-series has a unit root, is rejected.

* Statistically significant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

None of the time-series contain unit roots according to the results by the Augmented Dickey-Fuller tests and thus seem to be stationary. The most important criticism on the Dickey-Fuller tests is that their power is low if the process is actually stationary but contains a root which is close to the non-stationary boundary. Time-series that contain a root which dies down very slowly may not lead to a rejection of the null hypothesis using the Dickey-Fuller test. This

\textsuperscript{30} Dickey and Fuller, 1979. *Distribution of the Estimators for Autoregressive Time Series with a Unit Root*

\textsuperscript{31} Brooks, 2008. *Introductory Econometrics for Finance*
shortcoming however has no effect on the conclusions of the results in table 5.4 since the null hypothesis is in fact rejected for all methods. The results of these tests imply that the $t$-ratios as has been used to test the statistical significance of the raw data in table 5.3 are not disturbed by non-stationary data.

The most important conclusion in this paragraph is that the sample indicates a statistically significant upward trend in idiosyncratic risk over the entire sample period, even when the sample only represents periods of economic expansions. The next paragraph will cut the sample into different periods in order to analyze outcomes when sample periods vary.

5.2.2 Partial measurements

By means of graphical analysis different patterns could be observed in the CAPM results. As became clear by the studies of Bekaert et al. (2010) and Brandt et al. (2010) finding a trend depends amongst others on the time period of the sample. This paragraph therefore presents linear regression results based on varying sample periods.

Table 5.5 presents regression coefficients and their statistical significance for each measurement method for varying time periods. From the beginning of the sample, opening and closing dates of the sample periods have been shifted with periods of five year, keeping a minimum of ten years of data (excluding the final period 2001 – 2009). This led to 15 different periods starting in 1980, 1986, 1991, or 2001. The table exposes several results.

Firstly, the results can be compared to the finding by Bekaert et al. (2010) and Brandt et al. (2010) who conclude from the US market that lengthening the sample period beyond the year 2000 has an eliminating effect on the upward trend. In this sample however we can see in panels A through C that lengthening the sample period until 2005 or 2009 still results in a statistically significant upward trend. The conclusion from earlier work on the US market therefore seems not to apply to The Netherlands.

Secondly, we can see a transition in the sign of the beta coefficients. In the periods 1980 – 1990, 1980 – 1995 and 1986 – 1995 the betas appear to be negative indicating a downward trend. Furthermore in panel C we can see a very strong upward trend with high beta coefficients starting from 1991. This indicates a transition from a negative trend to an upward trend in the sample which lies between 1991 and 1995. This effect is also noticeable when looking at the last three columns in panels A through C. The beta coefficients get stronger when the sample starts in a later period. Looking at panel A and B the beta coefficients
immediately become positive and statistically significant when the period is extended until 2000, which is likely to be an effect of the dot-com bubble. The observation of the transition from a negative to an upward trend is in line with the conclusion on the graphs in section 5.1, indicating convexity.
Table 5.5: Linear trend regression beta coefficients (* 10^5) for various periods

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Bali et al. (2008)</td>
<td>-0.475</td>
<td>-0.387**</td>
<td>1.788***</td>
<td>1.083***</td>
<td>0.860**</td>
</tr>
<tr>
<td>CAPM Global Market Index</td>
<td>-0.966</td>
<td>-1.276***</td>
<td>2.832***</td>
<td>2.429***</td>
<td>2.696***</td>
</tr>
<tr>
<td></td>
<td>-0.367</td>
<td>-1.323***</td>
<td>1.660***</td>
<td>2.486***</td>
<td>3.434***</td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td>-4.195***</td>
<td>-4.485***</td>
<td>1.299***</td>
<td>1.343***</td>
<td>1.866***</td>
</tr>
<tr>
<td></td>
<td>-1.748*</td>
<td>-3.666***</td>
<td>0.490</td>
<td>1.534***</td>
<td>2.631***</td>
</tr>
<tr>
<td>Bali et al. (2008)</td>
<td>-1.019***</td>
<td>3.307***</td>
<td>1.410***</td>
<td>0.971***</td>
<td></td>
</tr>
<tr>
<td>CAPM Global Market Index</td>
<td>-2.199***</td>
<td>5.435***</td>
<td>3.459***</td>
<td>3.530***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-2.962***</td>
<td>3.156***</td>
<td>3.612***</td>
<td>4.657***</td>
<td></td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td>-5.123***</td>
<td>5.168***</td>
<td>3.266***</td>
<td>3.424***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-6.108***</td>
<td>2.517***</td>
<td>3.065***</td>
<td>4.203***</td>
<td></td>
</tr>
<tr>
<td>Bali et al. (2008)</td>
<td>7.502***</td>
<td>1.712***</td>
<td>0.924***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPM Global Market Index</td>
<td>12.242***</td>
<td>4.625***</td>
<td>4.296***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>8.872***</td>
<td>5.825***</td>
<td>6.559***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td>14.680***</td>
<td>5.394***</td>
<td>4.799***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>10.740***</td>
<td>6.262***</td>
<td>6.727***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bali et al. (2008)</td>
<td>-1.808**</td>
<td>-1.184**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPM Global Market Index</td>
<td>-2.231</td>
<td>1.088</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.603**</td>
<td>5.771***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td>-3.661**</td>
<td>0.432</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.995</td>
<td>4.836***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>2001 - 2009</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bali et al. (2008)</td>
<td>0.710</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAPM Global Market Index</td>
<td>2.658</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.928***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value Weighted Index</td>
<td>2.594</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.569***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
This table displays the beta coefficients that resulted from linear trend regression. Beta coefficients have been composed for different periods in the sample shifting five years at a time and maintaining a minimum of ten years of data (excluding the period 2001 – 2009). All beta coefficients are multiplied with 10^5 for displaying purposes. The significance of the coefficients is indicated by the number of asterisks:

* Statistically significant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

Thirdly, through time a shift in the importance of smaller firms in the sample can be seen. Using equal weighting, idiosyncratic risk is aggregated not considering the market values of the equities. When value weighting is used, the firm-specific risk is aggregated controlling for the market value of the company. Smaller companies thus have a much smaller impact in the value weighted measures. In the sample periods until 2000 value weighting mostly results in larger beta coefficients. However when the sample periods in panel A through C include the period from 2000 until 2005 or 2009, equal weighting results in larger beta coefficients. Also, in panel D and E value weighting mostly does not even yield statistically significant results where equal weighting does. This indicates that smaller firms have a larger impact on the upward trend in the 2000 – 2009 period than these firms had before. Furthermore it is also an indicator of smaller firms having more impact than larger firms on the upward trend in idiosyncratic risk in this period. One possible cause of this observation might be that Dutch firms as well started to issue equity earlier in their life cycle in that period as was the case in the US. Other possible causes can be found during the dot-com bubble and the credit crunch. During the dot-com bubble small businesses were similar to large businesses quickly expanding without being profitable, while it became clear after the burst that small companies have a hard time surviving on-line and appeared most vulnerable and risky. During the credit crunch large companies that were too big to fail received support from the government, whilst the small companies of course were never too big to fail. Especially these smaller companies that relied on external finance were, and are still, having a hard time receiving finance from financial institutions since banks increased their criteria for providing loans as they are perceived to be riskier.

The findings in this paragraph confirmed the observation of convexity as has been made in section 5.1, which is very different from the findings by Bekaert et al. (2010) and Brandt et al. (2010). Different as well is the existence of an upward trend even if the sample period

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32 Fink et al., 2005. *IPO Vintage and the Rise of Idiosyncratic Risk*
runs beyond 2000. Lastly the findings implicate a larger impact of smaller firms during the 2000’s. The next paragraph will discuss the differences in the various measures of idiosyncratic volatility.

5.2.3 Differences in idiosyncratic volatility measures

Using different measures for aggregate idiosyncratic risk yields different results. This paragraph will look into the difference between using value weighting or equal weighting, using the global market index or the value weighted index and using the CAPM method or the Bali et al. (2008) method.

Aggregating idiosyncratic risk using value weighting or equal weighting does not yield very large differences for the mean or standard deviation in this sample. The expectation based on earlier research in the US is that equal weighting would result in higher aggregate idiosyncratic risk due to the increase in impact of the smaller firms in the sample since these are perceived riskier. However in both CAPM results equal weighting yields a slightly lower average aggregate idiosyncratic volatility than by using value weighting. Kearney and Poti (2007) similarly did not find significant differences between both measures of aggregation in their research of idiosyncratic volatility in the European market.

The beta coefficients for equal weighting however are significantly larger. This is actually in line with earlier research in the US. As has been discussed in paragraph 2.3.2 and 5.2.2 small firms may have issued equity at an earlier stage in their life cycle than before. These companies are perceived to be riskier than the more established companies. It is not clear however whether the Dutch market is also subject to a substantial increase in smaller firms listing on its Amsterdam Stock Exchange or when this phenomenon would have started. Furthermore as became clear in paragraph 5.2.2 the larger coefficients are only an effect of the 2000 – 2009 period.

The CAPM method has been used with two different proxies for the market portfolio, the global market index (GMI) and the value weighted index (VWI). The GMI proxy results in a substantial lower mean and lower standard deviation than with the VWI proxy, however using GMI does result in larger beta coefficients. The VWI mean is closer to the results by Bekaert et al. (2010) however this is only one source of comparison. The superiority in

33 Bekaert et al., 2010; Brandt et al, 2009; Campbell et al., 2001; Wei and Zhang, 2006
results between the two proxy methods depends on which index is better in representing the true market portfolio. Since the true market portfolio should hold all available investments, the GMI results could be more trustworthy. The fact that a difference between both measures exist is not surprising since we have already seen that the correlation between both indices is only 0.65.

**Figure 5.3:** Aggregate idiosyncratic risk: CAPM Global Market Index vs. Bali et al. (2008)

This figure presents the aggregate idiosyncratic standard deviation as measured by the CAPM using value weighting with the Global Market Index as the market portfolio, and as measured by the method as proposed by Bali et al. (2008).

In their research, Bali et al. (2008) find significant lower values for their measure of idiosyncratic risk as compared to the measure by CLMX. The results by CLMX yield a 15% higher annualized standard deviation than resulted from the method by Bali et al. (2008). The reason for this difference is left unexplained. The CAPM annualized mean from this sample is about 88% larger than the annualized mean found using the Bali et al. (2008) method. The results by Bali et al. (2008) in this sample are also less volatile and show a far smaller upward trend. Figure 5.3 plots the CAPM global market index value weighted results and the Bali et al. (2008) results in one graph. It can be seen that although the Bali et al. (2008) results are lower, the time varying behavior looks the same. The larger difference in the measures in this paper is most probable an effect of the sample size. The model-independent measure relies on benefits of diversification in order to calculate aggregate idiosyncratic risk. Calculating the aggregate idiosyncratic risk for two assets will only result in very small values using this
measure since the benefits of diversification are relatively small. The CAPM method does make it possible to calculate idiosyncratic volatility even if the portfolio only contains two assets. The measure by Bali et al. (2008) therefore becomes more reliable when the sample size grows. In their paper, the sample contains over 2,000 assets in the beginning of the sample period and over 10,000 assets at the end whereas the sample used in this paper only contains 121 assets in total. Although it can be assumed that the incremental increase in reliance becomes smaller as the number of assets increase (since incremental benefits for portfolio diversification by adding more securities becomes smaller as well), it appears that due to the sample size in this research the model-independent measure by Bali et al. (2008) is less reliable than the CAPM measure.

This section covered the results based on the conducted research on aggregate idiosyncratic volatility. The next section will extend the already conducted research with the aim of finding determinants of the time varying behavior of idiosyncratic risk.

5.3 Determinants

In this section, which focuses on determinants, the sample has been split up in different portfolios to see the effect on idiosyncratic risk when assets have been grouped in a specific class. Earlier research relied primarily on regressions of determinants on idiosyncratic volatility in order to find the determinants that explain the time varying behavior of firm-specific risk in the best way. In this section however, portfolios have been formed based on the industry in which it is operating and based on company fundamentals. This method simplifies computations and allows for comparison between beta coefficients of linear regression between different portfolio sizes in order to identify different degrees of trends. Since the model-independent measure by Bali et al. (2008) becomes more inaccurate when the sample size is relatively small, this method will not be used in this section since it requires splitting up the sample in smaller portfolios. Hence Bali et al. (2008), as has been discussed in paragraph 5.2.3, would thus become even less reliable as a measure for idiosyncratic volatility.
### Table 5.6: Aggregate idiosyncratic standard deviation statistics per industry

<table>
<thead>
<tr>
<th>Industry</th>
<th>N</th>
<th>MV</th>
<th>Mean * 10^2</th>
<th>Standard deviation * 10^2</th>
<th>Linear regression Beta * 10^5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMI VW</td>
<td>GMI EW</td>
<td>GMI VW</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VWI VW</td>
<td>VWI EW</td>
<td>GMI VW</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMI EW</td>
<td>VWI EW</td>
<td>GMI EW</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMI EW</td>
<td>VWI EW</td>
<td>GMI EW</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMI EW</td>
<td>VWI EW</td>
<td>GMI EW</td>
</tr>
<tr>
<td>Industrials</td>
<td>25</td>
<td>4.4%</td>
<td>14.078</td>
<td>11.912</td>
<td>16.552</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.006</td>
<td>2.392</td>
<td>2.213</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4.576***</td>
<td>3.050***</td>
<td>3.396***</td>
</tr>
<tr>
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<td></td>
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<td>2.335</td>
<td>3.311</td>
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<td></td>
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<td></td>
<td>5.213***</td>
<td>3.824***</td>
<td>4.344***</td>
</tr>
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<td></td>
<td>2.410</td>
<td>1.895</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>2.193***</td>
<td>2.621***</td>
<td>0.730**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.702</td>
<td>1.999</td>
<td>1.847</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.488***</td>
<td>2.418***</td>
<td>1.998***</td>
</tr>
<tr>
<td>Technology</td>
<td>10</td>
<td>1.8%</td>
<td>19.812</td>
<td>20.241</td>
<td>21.549</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5.719</td>
<td>5.843</td>
<td>6.221</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4.163***</td>
<td>4.211***</td>
<td>4.171***</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>8</td>
<td>27.1%</td>
<td>11.478</td>
<td>13.490</td>
<td>15.196</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.050</td>
<td>1.794</td>
<td>2.368</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.618**</td>
<td>3.400***</td>
<td>-0.417</td>
</tr>
<tr>
<td>Other*</td>
<td>12</td>
<td>6.8%</td>
<td>13.599</td>
<td>17.575</td>
<td>16.585</td>
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<td></td>
<td></td>
<td></td>
<td>2.362</td>
<td>2.800</td>
<td>2.540</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.857***</td>
<td>3.986***</td>
<td>2.040***</td>
</tr>
</tbody>
</table>

This table reports statistics of the aggregate idiosyncratic risk categorized per industry. The industries are determined by DataStream’s industry codes. “Other” consists out of the industries Telecommunications, Basic Materials and Healthcare. The numbers of securities in the industries are presented by N. The average market value share of the industry compared to the market is presented by MV. Three panels are created to show the annualized mean, the annualized standard deviation and the beta as result of linear regression, of the idiosyncratic standard deviation. Results have been obtained using four different methods of CAPM measurements; Global Market Index – Value Weighting (GMI VW), Global Market Index – Equal Weighting (GMI EW), Value Weighted market Index – Value Weighting (VWI VW), and Value Weighted market Index –Equal Weighting (VWI EW). The significance of the coefficients is indicated by the number of asterisks:

* Statistically significant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level
5.3.1 Industry portfolios

The industry portfolios are based on the industry classification as has been reported by DataStream. Within each industry idiosyncratic volatility has been aggregated for both CAPM measurement methods, using both equal and value weighting. For the latter, new weights have been constructed based on the industry composition. Table 5.6 reports the annualized mean, annualized standard deviation and the beta coefficients from linear regression for each industry. Graphs can be found in the Appendix.

The interest in this paper goes out to the existence of a trend in idiosyncratic risk. Since an upward trend in The Netherlands has been confirmed in the previous section it might be interesting to see whether this is driven by a certain industry. The trend of idiosyncratic risk in a certain industry is measured once again by the beta coefficients derived from linear regression. All of these coefficients appear to be positive and statistically significant at the 1% level except for the Oil & Gas industry. Using value weighting for the Oil & Gas industry yields remarkable results. This is mainly caused by the securities of Royal Dutch Shell which has a relatively high market value. This market value causes the value weighted results to be almost fully influenced by only Royal Dutch Shell’s idiosyncratic risk and it is responsible for the high percentage of average market value share of the Oil & Gas sector.

Betas are highest for the Technology industry and the Financial industry, followed by the Industrials and Other industries. The Technology industry and the largest part of the Other industries (Telecommunications) have showed high varying regimes of idiosyncratic risk, especially during the dot-com bubble. Both industries however are relatively not very large in numbers and especially small in market value. The Financial industry however is both large in numbers as in market values and is presenting relatively high beta coefficients. Hence, the upward trend in idiosyncratic risk in the Dutch market is likely to be mostly driven by the Financial industry. The graphs in the Appendix show an upward trend for the Financial industry with values reaching an ultimate high during the credit crunch.

5.3.2 Company fundamentals portfolios

The fundamentals portfolios are based on variables as have been discussed in the literature review in chapter 2. These include Market value, Market-to-Book value, Return on Equity and Earnings per share.
Table 5.7: Aggregate idiosyncratic standard deviation statistics per determinant portfolio

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Mean * 10²</th>
<th>Standard deviation * 10²</th>
<th>Linear regression Beta * 10⁵</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GMI VW</td>
<td>GMI EW</td>
<td>VWI VW</td>
</tr>
<tr>
<td>4</td>
<td>12.609</td>
<td>12.408</td>
<td>15.470</td>
</tr>
<tr>
<td>Smallest</td>
<td>13.014</td>
<td>14.709</td>
<td>18.419</td>
</tr>
<tr>
<td>4</td>
<td>12.399</td>
<td>10.913</td>
<td>15.060</td>
</tr>
</tbody>
</table>
This table reports statistics of the aggregate idiosyncratic risk categorized per determinant portfolio. For each set, five portfolios have been created based on the size of the determinant, being Market value, Market-to-Book value, Return on Equity and Earnings per share. Three panels are created to show the annualized mean, the annualized standard deviation and the beta as result of linear regression, of the idiosyncratic standard deviation. Results have been obtained using four different methods of CAPM measurements; Global Market Index – Value Weighting (GMI VW), Global Market Index – Equal Weighting (GMI EW), Value Weighted market Index – Value Weighting (VWI VW), and Value Weighted market Index – Equal Weighting (VWI EW). The significance of the coefficients is indicated by the number of asterisks:

* Statistically significant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

For these four sets of fundamentals, yearly values have been retrieved from DataStream for all the assets in the data sample. The values of these determinants vary from year to year and complicate the creation of portfolios compared to the previous paragraph where companies stayed in the same industry. The value of a determinant in one year determines in which portfolio the asset will be placed in the next year. Therefore based on the available data yearly values have been composed for the 20\(^{th}\), 40\(^{th}\), 60\(^{th}\) and 80\(^{th}\) percentile to serve as portfolio boundaries. Based on these values assets were placed in a category ranging from 0 to 5. The categories from 1 to 5 contain the assets with the smallest until the largest fundamentals whereas 0 indicates that the determinant value of the previous year is unavailable.

This value might be unavailable due to the fact that the company was not listed yet, is delisted or because of unavailability in DataStream. In order to create the value weighted idiosyncratic risk within a portfolio weights had to be recalculated based on different portfolio compositions for each year. The use of this method allows the companies to change portfolio as their fundamentals change through time.

Similarly to the previous paragraph, idiosyncratic volatility has been aggregated for both CAPM measurement methods (using equal and value weighting) for each portfolio. Subsequently the annualized mean, annualized standard deviation and the beta coefficients from linear regression for have been created. The results can be found in table 5.7 and are graphically presented in figure 5.4. The table does not contain the size of the sample or the average market value since the composition of the portfolios change yearly.

Although the beta coefficients are different in size, all coefficients are positive and statistically significant at the 1% level. However by comparing sizes of the betas amongst the portfolios more information can be drawn from these regressions.
Figure 5.4: Graphical representation of determinant research results of fundamentals.

These eight graphs show betas, based on linear regression, and the annualized mean of idiosyncratic standard deviation for different sets of portfolios. For each set, five portfolios have been created based on the size of the determinant, being Market value, Market-to-book value, Return on Equity and Earnings per share. Betas have been presented as bars (scaled on the left y-axis) using both value and equal weighting for the CAPM measure. The upper four graphs use the Global Market Index as the market portfolio proxy and the lower four use the...
Value Weighted Index. Means have been presented as a line (scaled on the right y-axis) using value weighting.

The first fundamental value that has been researched is the Market value of the asset. The results based on the Global Market Index do not show a clear pattern when comparing the beta coefficients amongst the portfolios. The Value Weighted Index results however generally show a high beta coefficient for the portfolio with the smallest companies that decreases when moving up to a portfolio of larger companies. Moreover the pattern shows an exception for both aggregation methods but is quite clear when comparing the largest and smallest portfolio. Hence smaller companies seem to have a stronger upward trend in idiosyncratic risk than larger companies in the Dutch market. When market value is taken as a proxy for age, this effect might be caused by the new listings as described by Fink et al. (2005) who conclude that companies tend to issue equity in an earlier stage of their life cycles. This would mean that the smallest portfolio composition will change and will hold smaller companies as time goes by. These companies tend to be riskier and therefore the stronger upward trend could be explained accordingly.

The second fundamental value that has been covered is the Market-to-Book value. This item shows a mirroring effect compared to the market value. For both measures (GMI and VWI) an upward trend in beta coefficients can be spotted when moving to a larger portfolio. The smallest portfolio however seems to be an exception when value weighting is applied. This is due to the fact that this portfolio contains mainly technology firms together with a few other industry firms. The technology firms are relatively small in market value compared to other equities in the sample. Therefore the value weighted beta coefficient in the smallest portfolio is mostly determined by the few other firms of which contain outliers. When equal weighting is applied the technology firms do influence the results in such a way that a clear upward trend is visible. Hence the results indicate that firms with high market-to-book value (growth stocks) follow a stronger upward trend in idiosyncratic risk over time than firms with low market-to-book value (value stocks).

The third determinant is the Return on Equity. In their study, Wei and Zhang (2006) found an upward trend in idiosyncratic risk which was closely related to the downward trend in Return on Equity and the upward trend in the volatility of the Return on Equity. The latter however will not be discussed here. The beta coefficients resulting from the GMI method seem to be quite similar, showing no difference amongst the portfolios. The VWI method however did result in different values for the created portfolios. Although the differences are rather small
an upward movement can be detected. However the smallest portfolio is showing a higher beta when aggregated by equal weighting which is not in line with the other portfolios. This is probably a result of the smallest portfolio also containing firms with negative values of Return on Equity which does not result in similar behavior as small positive Return on Equity firms. The results therefore indicate that firms with high Return on Equity have a stronger upward trend in idiosyncratic risk than companies with low Return on Equity. Assuming that Wei and Zhang’s (2006) conclusion holds, this would indicate that firms with high Return on Equity exhibit the largest drop in Return on Equity and/or the largest increase in the volatility of this value.

Finally the Earnings per share have been used to form five value based portfolios. The results however seem to be exhibiting no pattern whatsoever on first sight. However, when it is taken into account that here as well the smallest portfolio contains negative values (which might disturb the beta coefficients), a sort of pattern becomes visible. Although the fourth portfolio value weighted results are the exceptions an upward movement can be identified. This might indicate that firms with high Earnings per share follow a stronger upward trend in unsystematic risk as compared to equities with low Earnings per share.

The results therefore show us that the trend in idiosyncratic risk in the Dutch equity market, all else being equal, is stronger for firms that have a low Market value, have a high Market-to-Book value, have high (or negative) Return on Equity, and/or have high (or negative) Earnings per share.

The next chapter will summarize the findings in this paper and will also give conclusions on the basis of these results.
Chapter 6

Conclusions

6.1 Summary conclusions

CLMX found an increase in idiosyncratic risk in the US market by studying stock returns for the period from 1962 until 1997. However by extending the sample period Bekaert et al. (2010) and Brandt et al. (2010) did not find an upward trend since the extension resulted in a decrease in idiosyncratic volatility from 2000 onwards, thereby presenting a concave pattern instead of an upward trend.

This paper is interested in the time varying behavior in the Dutch market, which according to Bekaert et al. (2010) has no significant upward or downward trend. 121 equities during the period 1980 – 2009 have been studied using a beta varying CAPM method and the model-independent method by Bali et al. (2008). The sample and methods used in this paper lead to new results.

First, the aggregate idiosyncratic risk seems to show spikes during the same periods as the US market. This observation is in accordance with the conclusion by Bekaert et al. (2010) stating that idiosyncratic risk is highly correlated across countries especially during crises. However the CAPM results exhibit a trend in idiosyncratic risk significantly different from the US market as found in earlier research. The CAPM results in this paper yield a convex trend whereas the US market is subject to an upward or concave trend. Bekaert et al. (2010) are possibly right in stating that a linear trend does not fit the time varying behavior of idiosyncratic risk. However when a linear trend is fitted to the entire sample period an upward trend is clearly visible even when the sample only presents periods of economic expansions. For the US market the upward trend was eliminated when the sample period was extended beyond the year of 2000.

Secondly, the Bali et al. (2008) method yields significantly different results compared to the CAPM method used in this paper which is not in line with the expectation which arose from the research done by Bali et al. (2008). However the method did resulted in quite similar time varying behavior of idiosyncratic risk. The larger difference in results is expected to be caused by the sample size since the reliance of the method increase as the sample size becomes larger.
Thirdly, the upward trend in idiosyncratic risk in the Dutch market is mostly driven by the Financial industry which has exhibited especially extremely high values during the credit crunch.

Finally, portfolios were created based on the size of fundamental values of the firms in the sample. The results showed that firms that have a low Market value, have a high Market-to-Book value, have high (or negative) Return on Equity, and/or have high (or negative) Earnings per share, have a stronger upward trend in aggregate idiosyncratic risk.

Overall, most striking is the upward trend in idiosyncratic risk in The Netherlands and its different time varying behavior compared to the US. The determinants of the time varying behavior of idiosyncratic risk as investigated in this research show similar results compared to earlier research. The discussions of determinants might have another spin as trends can be different across countries. It is necessary for these determinants to explain different trends internationally in order to be robust globally.

**6.2 Implications**

This section connects the results of the research to the literature review and especially to section 2.2 which explains why idiosyncratic risk matters.

In the case of investors holding insufficiently diversified portfolios a continuing trend in idiosyncratic risk is undesirable since these investors will be exposed to higher risk in the future. Furthermore investors looking to fully diversify their portfolios will need to include a larger number of assets since idiosyncratic risk has a positive effect on the number of assets necessary to obtain full diversification. Adding more assets goes hand in hand with an increase in transaction costs.

Arbitrageurs also suffer from a positive trend in idiosyncratic risk, since they are more exposed to the unsystematic risk.

The effect on the test statistics of event studies is negative as well. An increase in the idiosyncratic risk decreases the test statistic in these studies and therefore the statistical significance of the results decreases.

Finally, as already indicated in paragraph 2.2.2, a continuing upward trend in idiosyncratic risk has a negative effect on the value of options using the Black and Scholes-Merton model.
Although this paper identifies an upward trend in idiosyncratic risk, it is not sure whether this trend will continue in the future. Furthermore a linear trend might not even be the right fit. Therefore the actors involved in the implications as stated above should be aware of the time varying behavior of unsystematic risk and keep track of its movements. Furthermore undiversified investors, arbitrageurs or option holders should make their investment choices taking into account the results of the determinants research. Exposure to increasing idiosyncratic risk can be limited by selecting on fundamental values and industry.

6.3 Limitations

The conclusions and implications as discussed in this chapter should be considered in combination with the limitations of this research. Although the results of this paper are statistically significant the reader should consider the following drawbacks.

The first limitation of this research is the sample size of only 121 in total. Preferable would be to have a larger data sample in order for the statistical tests to be really robust. Especially in this research this is important since the sample size changes through time. Working with a larger sample could have also given more reliable results for the Bali et al. (2008) method. Unfortunately the Dutch equity market is not very large in numbers and therefore this problem is hard to overcome. By relaxing the selection criteria the sample size will become larger however this will also have a negative effect on the reliability of the data.

Secondly, in order to calculate idiosyncratic risk the CAPM has been used next to the model-independent method. The use of time varying betas has been an improvement over the CLMX method, however the use of multiple sophisticated asset pricing methods by for example including the Fama-French three factor model would have given more space for comparison and possibly more reliable results.

Thirdly, the PS statistic of Vogelsang (1998) has not been used to test for the existence of a trend. Instead linear regression has been performed on the data. It would be valuable to see if the results will still hold using Vogelsang’s (1998) PS statistic which is more reliable.

Finally, the impact of this research is rather small since it is only applicable to the Dutch equity market, which is relatively small when compared globally. Extending in-depth country research to other areas would be a valuable addition.
References


Appendix

Figure A.1a: Aggregate idiosyncratic standard deviation Industrials: CAPM Global Market Index

Figure A.1b: Aggregate idiosyncratic standard deviation Industrials: CAPM Value Weighted market Index
Figure A.2a: Aggregate idiosyncratic standard deviation Financials: CAPM Global Market Index

Figure A.2b: Aggregate idiosyncratic standard deviation Financials: CAPM Value Weighted market Index
Figure A.3a: Aggregate idiosyncratic standard deviation Consumer services: CAPM Global Market Index

Figure A.3b: Aggregate idiosyncratic standard deviation Consumer services: CAPM Value Weighted market
**Figure A.4a:** Aggregate idiosyncratic standard deviation Consumer goods: CAPM Global Market Index

![Graph showing consumer goods GMI with EW and VW lines](image)

**Figure A.4b:** Aggregate idiosyncratic standard deviation Consumer goods: CAPM Value Weighted market

![Graph showing consumer goods VWI with EW and VW lines](image)
Figure A.5a: Aggregate idiosyncratic standard deviation Technology: CAPM Global Market Index

Figure A.5b: Aggregate idiosyncratic standard deviation Technology: CAPM Value Weighted market Index
**Figure A.6a:** Aggregate idiosyncratic standard deviation Oil & Gas: CAPM Global Market Index

**Figure A.6b:** Aggregate idiosyncratic standard deviation Oil & Gas: CAPM Value Weighted market Index
**Figure A.7a:** Aggregate idiosyncratic standard deviation Other industries: CAPM Global Market Index

![Graph](image1)

**Figure A.7b:** Aggregate idiosyncratic standard deviation Other industries: CAPM Value Weighted market Index

![Graph](image2)