Return Predictability

Can correlation effectively predict returns?

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ABSTRACT

Previous research shows that index variance can be decomposed into average constituent correlation and average constituent variance. These studies hold that the average correlation captures features of the aggregate market risk and under a risk-reward relationship is a predictor of future excess returns. Based on these findings, this paper looks at contemporaneous and forecasting features of the risk variables, with market data from Eurostoxx50 and Swedish OMXS30. This study contributes to previous research by specifically studying the predictability of average correlation during market downturns and the conditional nature of risk and return. In accordance with previous research, the results confirmed that risk can be decomposed contemporaneously into average constituent correlation and average variance. When examining if average correlation is a predictor of future excess returns, a forecasting relationship is only found during market downturns, indicative of a conditional risk-reward trade-off. This is explained partly by the (i) Roll Critique, as different market proxies cause deviating results depending on the proxy's constituents, (ii) distinguishing changes in idiosyncratic risk from systematic risk as the risk proxy´s components vary over time, and (iii) the conditionality of market efficiency.

KEYWORDS: Average Correlation, CAPM, Roll Critique, Risk-Reward Trade-Off, Return Predictability

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Contents

1 Introduction

The relationship between risk and return has been a key concept in finance and asset pricing theory. Most literature state a positive relationship between the two factors, and a common proxy for risk is using either standard deviation or variance of returns. A common model capturing this trade-off is the Capital Asset Pricing Model, also known as the CAPM. This relationship relies not only on the accuracy of the CAPM, or the mean-variance trade-off, but also the proxy which is used to measure systematic risk and thus forecast future excess returns.

Using the research of Wilson & Pollet (2008) on this relatively narrow topic, this paper will examine if average constituent stock correlation is a predictor of future excess returns. This risk proxy will be studied both as a predictor of future excess returns, and contemporaneously to extend market knowledge about the underlying factors of the efficient market.

The underlying theories of the risk-reward dynamic will ultimately lead back to the Roll Critique, which states that the linear relationship between risk and return depend on the market portfolio being efficient and that they can be independently tested. Furthermore, the Roll Critique highlights that in any sample which acts as a proxy for the true market portfolio, the actual constituents still are of importance. Even if the proxies are correlated with each other and the market portfolio, the sample might exhibit market efficiency even if the true market is not efficient, and the other way around. This market portfolio identification problem is a limitation to the testability of the risk-reward dynamic. On the other hand, if individual stock returns share a sensitivity to market returns, an increase in correlation between the individual stocks could reveal an increase in the aggregate market risk. It is said dynamic that this paper aims to emphasize.

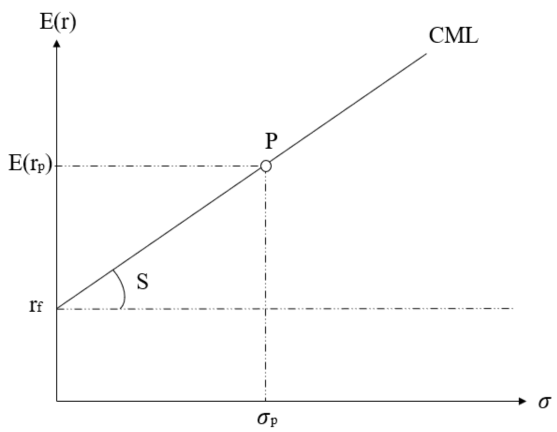
Wilson & Pollet (2008) show that the average correlation calculated of daily stock returns has forecasting features to future excess returns on a monthly and quarterly basis. They also show that if average correlation is held constant, changes in the stock market risk can be interpreted as the changes in average variance of individual stocks. These changes in average individual variance have a negative relationship with future excess stock returns, indicating that they are of idiosyncratic nature. Based on the findings of Wilson & Pollet (2008), this paper examines (i) the contemporaneous index variance and whether it can be decomposed into constituent variance and correlation, (ii) if lagged average constituent stock correlation is a predictor of future excess returns, (iii) if lagged average constituent stock correlation is a predictor of future excess returns during market downturns. This is studied using market data from Eurozone Eurostoxx50 and Swedish OMXS30.

In accordance with Wilson & Pollet (2008), the results confirmed that risk can be decomposed contemporaneously into average constituent correlation and average variance. When examining if average correlation is a predictor of future excess returns, a forecasting relationship is only found during market downturns, indicative of a conditional risk-reward trade-off. This is explained partly by the (i) Roll Critique, as different market proxies cause deviating results depending on the constituents, (ii) distinguishing changes in idiosyncratic risk from systematic risk as the risk proxy´s components vary over time (iii) the conditionality of market efficiency.

2. Theoretical Background

The paper aims to examine a risk-reward relationship where average stock correlation together with average stock variance act as a risk proxy in forecasting future excess returns. Revising the fundamentals of the risk reward trade-off, the Capital Market Line (CML) represents the possible combinations of risk and expected return, Berk & DeMarzo (2014). The increase in risk will subsequently increase the expected return the investor requires as compensation for holding the risky asset. The investor will then allocate his funds along the capital market line, ranging from risk free assets (such as T-bills which commonly are utilized in such an example), to a risky portfolio, depending on investor risk appetite. This relationship is illustrated below.

Graph 1 – Capital Market Line



The slope of the CML is known as the Sharpe Ratio, *S*, given by the equation below:

$$S = \frac{(E(r_p) - r_f)}{\sigma_p} \tag{1}$$

Where S represents the Sharpe ratio, $(E(r_p) - r_f)$ the expected excess return on the portfolio and σ_p the standard deviation of the portfolio.

All other things held equal, the investor would prefer a steep-sloping capital market line, as this would maximize the increase in expected return per each level of increasing risk.

This model is a good overview and introduction to the risk-reward trade-off, and why an accurate estimate of risk is important to the investor. Under CAPM assumptions, an efficient portfolio can be identified, and the risk-reward trade-off is established as:

$$E(R_i) = r_i = r_f + \beta_i \times (E[R_{mkt}] - r_f) \quad (2)$$

Where $E(R_i)$ is the expected return on investment, r_f the risk-free return, β_i the beta of the security with respect to the market portfolio (volatility due to systematic risk) and $(E[R_{mkt}] - r_f)$ the expected excess market return.

3. Theory & Previous Literature

3.1 The Accuracy of the Capital Asset Pricing Model

The ability of average stock correlation and average variance to predict future excess returns, relies on the accuracy of the theory that there is a fundamental risk-reward or mean-variance trade-off in the market. This relationship can be found in one of the most fundamental asset pricing models in finance, the CAPM, which relies on the variance in mean relationship[3]. Despite the risk-reward being an assumption in the efficient market, it´s accuracy has been studied for decades with only limited success, by amongst others Campbell (1987) and Glosten, Jagannathan & Runkle (1993), which both find a negative relationship between variance and excess expected return. The model has faced direct criticism, nonetheless from Black, Jensen & Scholes (1972) which amongst other things points out that low beta assets earn a higher return on average, and high beta assets earn a lower return on average than forecasted by the CAPM model. This potential lack of accuracy in the mean-variance relationship can be one of the reasons further research using systematic risk as a predictor of returns lack explanatory power.

Merton (1973) also points out that the CAPM is a static model, although it is often applied as an intertemporal model, which points to further critique of the validity of the CAPM relationship when applied over time. Merton shows that in a number of examples, the portfolio behavior of an intertemporal maximizer will be significantly different than that of a constant one. This leads to a second conclusion that the validity of the mean-variance relationship holds different amount of explanatory power over time and is therefore dependent of varying economic conditions. The intertemporal model which Merton deduces for the investor which acts to maximize expected utility of lifetime consumption continuously, is referred to as the Intertemporal Capital Asset Pricing Model, henceforth the ICAPM.

Looking further at the accuracy of the risk-reward trade off, Wilson & Pollet (2008) refer to the Roll Critique, Roll (1976), where amongst several conclusions, CAPM is criticized on the fact that the linear relationship between expected return and beta, depends on the market portfolio being efficient and that they can be independently tested, which the Roll Critique proposes is not the case. Furthermore, the Roll Critique highlights that in any sample which acts as a proxy

[3] For more research on the positive relation of expected risk premium and volatility, please see French, Schwert & Stambaugh (1986)

for the true market portfolio, the actual constituents still are of importance. Even if the market proxies are correlated with each other and the market portfolio, the sample might exhibit market efficiency even if the true market is not, and the other way around. This market portfolio identification problem is a limitation to the testability of the risk-reward dynamic.

3.2 Proxies for Risk

The relationship between risk and return has been a key concept in finance and asset pricing theory. Most literature state a positive relationship between the two factors, and a common proxy for risk is using either standard deviation or variance in returns. Bali, Cakici, Yan & Zang (2005) state that despite literature using these measures of risk, there is no clear consensus regarding the validity of these parameters. In particular, Bali et al. (2005) refer to a study conducted by Goyal & Santa-Clara (2003), in which the authors find that the lagged equal-weighted average stock variance correlates positively with value-weighted portfolio returns. In other words, Goyal & Santa-Clara´s (2003) results support the theory of a risk reward trade off, where increased variance in period *t-1* implies increased excess returns in period *t*. On the other hand, Bali et al. (2005) contradict their findings by showing the effect of a liquidity premium distorting the variance measure when equal-weighting larger and smaller market capitalized stocks amongst the constituents, in the predictive regressions. By extending the sample data for a longer period and replicating Goyal & Santa-Clara´s (2003) study, Bali et al. (2005) show that the lagged equal-weighted average stock variance is not a significant predictor of future value-weighted excess portfolio returns.

Nonetheless, the risk reward theory remains central in asset pricing theory, and has within trading strategy and financial market efficiency studies been a core concept. Expanding the theory on what can be considered an accurate risk proxy, Wilson & Pollet (2008) find that changes in aggregate risk may be distinguished in the change in correlation between individual stock returns in the market. Since the return on the market portfolio is a component of most stock returns, an increase in market risk, all other things equal, would be associated with an increased tendency of stock prices to move together. As a result, such increases in correlation represents increases in true aggregate market risk. Assuming an efficient market, if stock market premium depends positively on aggregate market risk, then the average correlation between stock returns should forecast future excess market returns. Wilson & Pollet (2008) find that the average correlation of the S&P500 constituent stocks forecast future excess returns on a monthly and quarterly basis. The reason being, that if average correlation captures market shocks and aggregate market risk, based on a risk-reward trade-off, correlation should forecast future stock market excess returns.

The different theories of how to capture market risk to determine future returns are debated, and nonetheless important for the topic. Wilson & Pollet (2008) refer to both Bali et al. (2005) and Goyal & Santa-Clara (2003) when looking at variance as a proxy for risk, and present results closer to Bali et al. (2005), and at odds with Goyal & Santa-Clara (2003). Wilson & Pollet (2008) show that average constituent variance itself does not predict future excess returns, but when index variance is decomposed into average constituent variance and correlation, this variable is a predictor of future excess returns.

The topic of looking at correlation as a proxy for risk and a variable which has forecasting features is a relatively narrow topic. Longin & Solnik (1995) have contributed to this field with their investigation of correlation between international stock markets by using monthly return data. In contrast to previous theory, which had assumed constant correlation over time, Longin & Solnik (1995) found that correlation in general increased over time, as well as a tendency for correlation to increase during periods of high volatility in the market. Longin & Solnik (2001) find that this is not necessarily the case, and that *market trends* matter more when relating to correlation. More specifically they find that correlation increases in bear markets, but not during bull markets. This finding is shared by Hong, Tu & Zhou (2007) as well as Ang & Chen (2002), where the former conclude that stocks more often move together when the market goes down, and the latter that correlations between U.S. stocks increase during downside trends and especially for extreme downside market moves. By applying extreme value theory to model the multivariate distribution tails, the distribution of extreme correlation for stock returns is derived. Longin & Solnik (2001) find that the negative tail of this distribution does not show multivariate normality, but the positive tail does. Thus the conclusion is made that average stock correlation not only is time-varying but also trend varying. Longin & Solnik's (2001) conclusion that correlation is time varying, is fundamental to this paper, as average correlation is used as a variable to predict future excess returns.

On the same topic on how correlation varies with time, it is also worth mentioning Cochrane

(2011)[4], which studies the effect of time varying discount rates, which in turn would factor into CAPM to change the mean-variance relationship. This relationship will not be discussed in this study, but would be an interesting next step to investigate.

3.3 Correlation as a Risk Proxy

The main theoretical background for this paper builds on Wilson & Pollet (2008), and their contribution to quantitative research by showing the importance of correlation when predicting future excess returns. By decomposing market variance into average stock variance and correlation, they prove that average correlation between constituent stock returns predict subsequent excess stock market returns. Wilson & Pollet (2008) also show that if average correlation is held constant, changes in market risk can be interpreted as the changes in average variance of individual constituent stocks. These changes in average individual variance are negatively correlated to future excess returns, indicating they are of idiosyncratic nature, if referring to Bali et al. (2005).

Wilson & Pollet (2008) highlight that when a market proxy is used, only a subset of aggregate market wealth is captured, referring to amongst others, Roll (1976) and the Roll Critique. Therefore the ability to accurately observe the true market variance interferes with the empirical relationship in CAPM and the risk-reward trade-off. Despite this, Wilson & Pollet (2008) find that average stock correlation can predict future excess stock market return for the S&P500, and do so better than average stock market variance. The authors use a logarithmic version of CAPM based on the assumption that returns are log-normally distributed. The results indicate that changes in the market variance of daily returns are almost completely captured by the product of average stock correlation and variance.

The model for expected returns used by Wilson & Pollet (2008) is based on Campbell & Viceira´s (2002) model of asset returns, where the expected excess returns on a risky asset follow a conditional log-normal distribution:

$$E_t\left[r_{i,t+1}\right] - r_{f,t+1} + \frac{\sigma_{i,t}^2}{2} = \gamma \sum_{j=1}^{N} w_{j,t}^* \sigma_{ij,t} \qquad (3)$$

[4] For more information on time varying discount rates, please see Cochrance (2011)

Where $w_{j,t}^{*}$ is the optimal weight of asset *j*, in the portfolio, $r_{f,t+1} = \log(1 + R_{i,t+1})$ is the log return for asset i , $r_{f,t+1}$, is the log return on the risk-free asset at *t*, γ is the investors coefficient of relative risk aversion, $\sigma_{i,t}^{2}$ the conditional variance, $\sigma_{ij,t}$ the conditional covariance for log returns. The time *t* subscript for conditional variance and covariance, indicates that both parameters possibly are time-varying, as defined by Wilson & Pollet (2008).

From this model, an approximation for the log return of a portfolio is used, in terms of the log returns of the constituents and the portfolio weights.

$$E_t\left[r_{i,t+1}\right] - r_{f,t+1} + \frac{\sigma_{i,t}^{2}}{2} \approxeq \gamma \sigma_{im,t} \tag{4}$$

Here the expected excess log return for asset *i* is proportional to the conditional covariance of the return for asset *i* with the return of the market portfolio, hence the logarithmic version of CAPM holds. Where the return on asset *i*, $r_{i,}$ will equal the observable stock market, r_s. These assumptions on the structure of the stock market returns will be the basis for the variables derived later in the methodology section.

Similar to Wilson & Pollet (2008), this paper examines the explanatory power of average constituent correlation in the market risk proxy. Driessen, Maenhout and Vilkov (2009), study whether exposure to average correlation in the stock market, affect market returns. If so, assets that pay off well when market correlations are higher than expected, earn higher returns than can be justified by their exposure to other priced risk factors. For this question the authors use index options to investigate, as this is a good example of an asset which would appear expensive if correlation risk is priced. The authors conclude that the high risk premium earned when writing stock index option, compared to the low or zero risk premium earned when writing individual stock options, can be explained by the price of correlation risk being larger than individual stock variance.

Driessen et al. (2009) collect this evidence for a correlation risk premium by decomposing changes in individual stock variances and changes in stock correlation, so that individual variance risk and correlation risk is priced. Using the S&P100, the authors find that unlike the estimated variance risk premium in individual options (which is positive on individual variance risk), a large negative index variance risk premium is found for writing the index option. This would point to that the average correlation of an index is priced.

An option based trading strategy is also implemented to test the theory, which is aimed at exploiting priced correlation risk. The strategy sells index straddles and buys individual straddles and stocks in order to hedge individual variance risk and stock market risk. The strategy results in an attractive risk return and correcting for standard risk factors, offers an excess return of more than 10% per month. This would indicate evidence of a correlation risk premium.

The decomposition of risk into average stock correlation and average stock variance may at first be misleading as previous research may point to the predictive power of correlation to future market variance, i.e. that these are dependent variables and affect each other. To analyze average correlation, market variance needs to be decomposed. Driessen, Maenhout and Vilkov (2009), as well as Wilson & Pollet (2008) decompose market variance into average constituent variance and correlation, where the risk premium can be decomposed in a similar way.

Below is Driessen et al.'s (2009) study of index and individual variance risk premium, where the left hand side represents index variance risk premium, the first term on the right hand side is the individual stock variance risk premium and the final term is the correlation risk premium.

$$E_t^Q[d\emptyset_I^2] - E_t^P[d\emptyset_I^2] =$$
$$= \sum_{i=1}^{N} \iota_i\{E_t^Q[d\emptyset_i^2] - E_t^P[d\emptyset_I^2]\} + \sum_{i=1}^{N}\sum_{j\neq i} w_i w_j \emptyset_i\, \emptyset_j\{E_t^Q[d\rho_{ij}] - E_t^P[d\rho_{ij}]\} \tag{5}$$

This relationship is important to the thesis of average correlation forecasting excess returns, as it shows empirical evidence of how correlation risk premium relates to both index variance and average constituent variance.

3.4 Conditional Relationship of Risk & Return

Going back to the question if risk can have forecasting power when looking at the average excess daily return, economic conditions play a rather significant role. Wilson & Savor (2014), show that stock market risk premium, and the relation between beta and average excess returns is positive during times when macroeconomic data is scheduled to be announced. Most previous studies find no direct relation between beta and average excess returns, i.e the risk-reward trade-off, but Wilson & Savor (2014) show that asset prices behave differently during days when macroeconomic news is scheduled to be announced.

The authors find that compared to the average trading day, the announcement day risk premium is highly statistically significant and robust, showing higher average excess return and showing higher significance for a risk-reward trade-off. Formally, this shows that on days when macroeconomic data is scheduled to be announced, the risk-reward relationship has higher significance, thus raising the question if the relationship is conditional and dependent on market conditions. A possible reason for this is suggested; that on days when macroeconomic announcements are scheduled, the investor requires higher reward to hold higher risk assets, a shift which affects the market risk-reward trade-off. The main results include the conclusion that expected variance is positively correlated with future announcement day returns on, i.e. market efficiency could be conditional.

This is in line with several previous studies which conclude that CAPM holds in a conditional sense, i.e. that beta and stock market premium vary over time, by amongst others Jagannathan & Wang (1996). Hence the relative efficiency of a potential risk proxy would therefore also be conditional and vary over time.

4. Data

To measure the correlation and variance of the indices' constituent stocks, market proxies were created using the constituents in Eurostoxx50, starting October 1st 1998, and OMXS30, starting October 1st 1998. These datasets include the daily returns for the constituents of the Eurostoxx50 index and the OMXS30 index. Data for these indices were collected both from Bloomberg Terminal and Reuters Datastream. All index constituent changes were manually adjusted for the relevant period Oct-1998 – Mar-2018. All changes are recorded (see Appendix). Price indices are reported, as it is calculated solely on constituent returns, which implies that no dividends have been reinvested during the time period. This represents the capital gains component, as the daily stock movements are of interest, to study the predictability of average correlation.

Furthermore, data for 1-month floating EURIBOR was collected, and used as a proxy for the risk-free rate to determine excess market return. While the EURIBOR might not be an optimal proxy, the fluctuations of the rate will nonetheless likely capture the fluctuations of the true risk-free rate and the effect on the regression is deemed to be minimal. EURIBOR data was collected from Reuters Datastream. Data for Eurozone seasonally adjusted GDP change was collected from the ECB database to use as a determinant of market conditions. The seasonally adjusted GDP is used to adjust for cyclicality, as this study aims to identify market downturns to test the conditionality of the risk-reward trade-off. GDP data is reported on a quarterly basis and the study primarily looks at a monthly frequency, hence it is assumed that all months where the quarterly adjusted GDP growth is negative also are negative.

The risk-free rate for the OMXS30 index is the monthly rate for a Swedish 1-month T-bill from the Fama-French factor dataset from Swedish House of Finance. Data for the Swedish seasonally adjusted GDP was collected from the SCB database.

4.1 The Eurostoxx50

The index covers 50 stocks from 11 Eurozone countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The constituents in the index are decided by the floating market cap of blue chip stocks in the Eurozone universe. The 50 stocks which are largest by market cap are included in the index, and once a year a review is conducted to reconstruct the index in Q3. Finally, the index follows an additional rule of fast entry and fast exit, where a constituent is deleted from the index if it ranks below nr 75 on the market cap ranking, and the stock next in line for the top 50 is added. A deleted stock is replaced immediately to maintain the fixed number of stocks.

The indices' calculations are based on a Laspeyres formula, which measures price changes against a fixed-base quantity weight:

$$I_t = \frac{\sum_{i=1}^{n}(p_{it} * s_{it} * ff_{it} * cf_{it} * x_{it})}{D_t} = \frac{M_t}{D_t} \tag{6}$$

Where *t* is the time when the index is computed, *n* in the number of constituents in the index, p_{it} is the price of company *i* at time *t*, s_{it} is the number of shares of company *i* at time *t*, ff_{it} is the free float factor of company *i* at time *t*, cf_{it} the weighting cap factor of company *i* at time *t*, x_{it} the exchange rate from local currency into index currency, D_t the divisor of the index at time *t*, and M_t the free float market capitalization of the index at time *t*.

The Eurostoxx50 – Practical limitations

The Eurostoxx50 index uses a more complex weighting procedure to derive its index than above illustrated. Instead of the free-float market capitalization methodology, Eurostoxx excludes additional institutional holdings from its calculations. Furthermore, Eurostoxx applies a liquidity multiple depending on how liquid the constituent stock is. These metrics applied to calculate the correct weighting are both proprietary and hence cannot be included in the calculation. Eurostoxx also adjusts the weighting so that no constituent can contribute more to the total weighting than 10% at time *t.* As such each constituent, *i*, was assigned an adjusted weight,$W_{i,t}$, in each time *t*, where the excess weight contributed by any stock where $W_{i,tt}$ > 10% was portioned out to the other constituents.

$$W_{i,t} \begin{cases} 10\% & W_{i,t} \geq 10\% \\ W_{i,t} & W_{i,t} \leq 10\% \end{cases} \tag{7}$$

This loop was repeated until no stocks had a weight above 10% for each time *t* in the data time series.

Data availability issues for the Eurostoxx50 Index

Data for the market capitalization for certain constituent stocks were missing, especially in the earlier years of the time series. These stocks were assigned a market capitalization equal to the lowest market capitalization among the other active constituents, at the point when the stock enters the index. The market capitalization then develops as a function of the returns for the constituent. It is assumed that the company undertakes no managerial actions, i.e. no dividends, share buybacks or any other type of equity issuances, affecting the market capitalization. An alternative approach would be to delete these constituent stocks when replicating the index. However, as the weight of each constituent is a function of the percentage of the total market capitalization for Eurostoxx50, calculated as the aggregate market capitalization for all constituent stocks at that time, excluding a constituent stock would distort the weight assigned to all other stocks.

The following example is provided; an index consists of 4 stocks, these stocks have the true market capitalization, $S_1=10$, $S_2=20$, $S_3=50$, $S_4=20$. However, S_4*'s* market capitalization is unknown. If S_4 is excluded from the weighting calculations, the weight for S_1 would equate

$W_1 = 12,5\%$. If S_4 is included and assigned a market capitalization of 10 equal to the lowest market capitalization of the know market capitalization for other constituent stocks, the weight for S_1 would equate $W_1 = 11,1\%$. The true $W_1 = 10\%$, had the weighting been computed with the correct market capitalization for S_4. Not including S_4 would distort the weights to a greater extent, than if S_4 is included with an assigned market capitalization of 10. While neither method is optimal, assigning a value is more accurate. The reason the lowest value is assigned, is because that implicitly becomes the threshold market capitalization required to be part of the index. Manual adjustments made reported in the appendix.

4.2 The NASDAQ OMX Stockholm 30

The NASDAQ OMX Stockholm 30 index calculates and reweights the index in real-time. The index is calculated using the formula below.

$$I_t = \frac{\sum_{i=1}^{n} q_{i,t} * p_{i,t} * r_{i,t}}{\sum_{i=1}^{n} q_{i,t} * (p_{i,t-1} - d_{i,t}) * r_{i,t-1} * j_{i,t}} \tag{8}$$

Here I_t is the index level at time *t*, $q_{i,t}$ is the number of shares of company *i* in the index at time *t*, which is the current number of outstanding shares. $p_{i,t}$ is the price quote currency of a share in company *i* at *t*, $d_{i,t}$ is the dividend used for total return indices, $r_{i,t}$ is the foreign exchange rate of index quote currency to quote currency of company *i* at time *t* (where needed). $j_{i,t}$ is an adjustment factor for corporate actions.

The index has fast entry and fast exit rules, the periodic review is conducted on the basis of figures after closing on the last trading day of October and April by NASDAQ OMX. A deleted stock is not necessarily replaced immediately. As a result, the active constituents in the OMX index might vary between 27 – 30 stocks for each trading day, *t*.

4.4 Data period and frequency

The complete period ranges from October 1998 to March 2018. The reason for the selection of the data period is that the Eurostoxx50 index was created in 1997. During the first year, the Eurostoxx50 exhibited strange movements and data is scarce on which constituents constituted the index at the time. While data is available further back in time for the OMXS30 index, the same time period was chosen to increase comparability between the two data sets and avoid potential data snooping. Results are reported on a monthly frequency.

Complete period

I. October 1998 – March 2018

To test whether the predictability of average correlation and the risk-reward trade-off is conditional on market conditions, two sub-periods have been devised. The main devisor for market conditions is the seasonally adjusted GDP in the Eurozone and Sweden for the Eurostoxx50 and OMXS30 index respectively. As these are not the same periods for the indices, a complementary definition of what constitutes a common market downturn is reported as a control time period. A dummy variable has been created to collapse the different sub time-series constituting a market downturn into a consecutive time series.

Periods during which the seasonally adjusted GDP growth was negative for the Eurozone

i. January 2003 – March 2003
ii. April 2008 - June 2009
iii. April 2011- June 2011
iv. October 2011 – March 2013

Periods during which the seasonally adjusted GDP growth was negative in Sweden

i. July 2001 - September 2001
ii. March 2002 - May 2002
iii. January 2008 - March 2008
iv. October 2008 - March 2009
v. October 2011 – December 2011
vi. July 2012 – December 2012
vii. April 2013 – June 2013

While the same criterion is used to define what constitutes a market downturn, an alternative definition is provided below, to increase comparability between the two datasets and avoid potential data snooping.

Alternative market downturn definition

i. Dotcom Crisis

March 2000 – October 2002

Defined as the bear market during and post the dotcom market crash in late March until the recovery in late 2002.

ii. Subprime Crisis

August 2007 – June 2009

Defined as the bear market from when the subprime crisis started to unfold, and financial institutions started to default in late 2007, until mid-2009 when the stock market started to show signs of recovery.

iii. Sovereign Debt Crisis

June 2011 – December 2012

Defined as the period post S&P´s downgrade of Greek sovereign bonds to junk bonds during June 2011 until gradual recovery in late 2012.

5. Methodology

5.1 Equal-weight vs value weight

One of the main critique articulated by Bali, Cakici, Yan and Zhang (2005) against Goyal and Santa-Clara (2001), is that by only looking at the equal-weighted variance as a predictor of value-weighted portfolio returns on the NYSE/AMEX/Nasdaq stocks, the liquidity premium is not taken into account. The positive relationship proven by Goyal and Santa-Clara (2001) was mainly due to variance being overstated, as less liquid and subsequently more volatile stocks, were equally weighted to liquid and less volatile stocks. Even though Bali et al. (2005) and Goyal and Santa-Clara (2001) only discuss average variance as a predictor, the critique could be deemed valid against using an equal-weighted average correlation variable as a predictor of excess portfolio return, as the liquidity premium would likely distort the correlation as well. However, unlike Nasdaq, the Eurostoxx50 index used in this study comprises only the largest blue-chip stocks in the eurozone area. The market capitalization for many of the constituent stocks is not available for the full period of the data sample. Hence equal-weighted regressions are reported in the appendix, to show that the manual adjustments done to the value-weighted data variables did not have any qualitative implications for the results.

5.2 Average constituent variance

The average variance among all constituents in the Eurostoxx50 and OMXS30 index are key components of the forecasting regression. The daily sample variance of returns is calculated for each active constituent on a rolling basis, where Dt is the number of trading days in each month. The daily sample variance is thus given by

$$\hat{\sigma}_{i,t} = (\frac{1}{D_t - 1}) \times \sum_{d=1}^{Dt}\big((1 + R_{i,d}\big) - \frac{1}{Dt} \times \sum_{d=1}^{Dt}(1 + R_{i,d}))^2) \tag{9}$$

To compute the average variance. $W_{i,t}$ is defined as the weight that stock *i* represents of the total index at time *t*. Due to the specific rules of the Eurostoxx50 and OMXS30 index and the "fast entry & exit rule" especially, some firms are excluded and added into the index mid-month. In order to have the same amount of data points of daily returns constituting the variance calculation, these stocks are excluded from the computation of the average variance in period *t*, instead only the active constituents in period *t* are included, defined as *At*. Opening market capitalizations are used in the weighting procedure. For the value-weighted average variance for the stock index it is computed as the market capitalization of stock *i* over the total market capitalization of the active components for the index as a whole. Whereas in the computation of the equal-weighted average variance each stock is assigned a weight so that the sum of all weights assigned equal to 100% in each period.

$$AV_t = \sum_{i=1}^{At} w_{i,t} \times \hat{\sigma}_{i,t}^2 \tag{10}$$

5.3 Average constituent correlation

The daily conditional covariance at time *t* is calculated pairwise for all possible combinations in the index. As some stocks are excluded and others consequently included in the index mid-month, only the active constituents A_t where data points for all trading days in the month are available, are included. As $At \leq 50$, the total available combinations at any time *t* will never exceed 1225. The estimator for covariance for stocks *i* and *j* in period *t* is given below:

$$\hat{\sigma}_{ij,t}^2 = \left(\frac{1}{Dt-1}\right) \times \sum_{d=1}^{Dt}\left((1+R_{i,d}) - \frac{1}{Dt} \times \sum_{d=1}^{Dt}(1+R_{i,d})\right) \times \left((1+R_{j,d}) - \frac{1}{Dt} \times \sum_{d=1}^{Dt}(1+R_{j,d})\right) \tag{11}$$

On average there are 20.95 trading days in every month in the dataset. The daily covariance and variance is thus multiplied by 21, to get the variables in a monthly frequency. Henceforth variance and covariance will be denoted as monthly and not daily. The correlation is calculated using the Pearson product-moment correlation coefficient, which is measured at the last trading day for each month, using all trading days in the month as basis.

$$\hat{\rho}_{ij,t} = \frac{\hat{\sigma}_{jk,t}}{\hat{\sigma}_{j,t} \times \hat{\sigma}_{k,t}} \tag{12}$$

The average monthly correlation is thus estimated as

$$AC_t = \sum_{i=1}^{At} \sum_{i \neq j} w_{i,t} \times w_{j,t} \times \hat{\rho}_{ij,t}$$

(13)

The value-weighted average correlation for the stock index is computed as the market capitalization of stock *i* and stock *j* over the total market capitalization of the active components for the index as a whole. Whereas in the computation of the equal-weighted average correlation each stock is assigned a weight so that the sum of all weights assigned equal to 100% in each period.

5.4 Index return

A value-weighted and equal-weighted basket based on the daily returns of the constituent stocks are created for Eurostoxx50 and OMXS30, henceforth referred to as the value-weighted and the equal return respectively for each index. The returns for the active constituent stocks in the index at time *t* is calculated as below:

$$R_{EW,t} = \frac{\sum_{i=1}^{At} R_{i,t}}{At_{t-1}}$$

(14)

$$R_{VW,t} = \sum_{i=1}^{At} w_{i,t} \times R_{i,t}$$

(15)

5.5 Index variance

The sample variance for the index is calculated based on the daily returns for all previous days in the month. As with the average variance and covariance measures, it is multiplied by 21, the average number of trading days in each month for the data set, to estimate the monthly variance. The sample index variance based on index returns *k,* is calculated as follows:

$$Var - I_t = (\frac{1}{D_t - 1} \times \sum_{d=1}^{Dt} \left((1 + R_{k,d}\right) - \frac{1}{Dt} \times \sum_{d=1}^{Dt} (1 + R_{k,d}))^2)$$

(16)

To test whether the index variance can be decomposed, an alternative approximation methodology is presented inspired by Wilson & Pollet (2008). As previously discussed in the literature overview, Wilson & Pollet (2008) provides mathematical evidence supporting the decomposition. The index variance should thus be a function of the average correlation and average variance of the stock constituents at any point in time. Implying that index variance can be captured by:

$$Var_{s,t} = b_0 + b_1(AC_t \times AV_t) + \varepsilon_t \tag{17}$$

While Wilson and Pollet (2008) argue that the mean of errors will not equate to 0 given $AC_t \times AV_t$, as a result of issues regarding measurements errors and the exclusion of the sum of squared weights from the AC calculations. As such the coefficient b_1 might not equate to 1. In order to derive an additional proxy for market risk, the multiplicative variable will be used.
Albeit the variable will not capture all of the index variance, it will serve as an additional measure of risk. The multiplicative variable is defined as:

$$Var - M_t = AC_t * AV_t \tag{18}$$

5.6 Overview of variables

A summary of all variables used in the regressions are presented below;

Average correlation: The average correlation for all active constituent stocks calculated at each month's end, based on all daily return data in that month. Covariance and variance multiplied with 21 to get monthly frequency. Reported as equal-weight, value weight and median.

Denotation: $\text{AC}_{\text{(Index), (Weighting), (Time)}}$

Average variance: The average variance for all active constituent stocks calculated at each month's end, based on all daily return data in that month. Variance multiplied with 21 to get monthly frequency. Reported as equal-weight, value weight and median.

Denotation: $\text{AV}_{\text{(Index), (Weighting), (Time)}}$

Index variance calculated as the factor of average correlation and variance multiplied: The variance for the index calculated as the average constituent correlation multiplied with the average constituent variance.

Denotation: $\text{Var-M}_{\text{(Index), (Weighting), (Time)}}$

Index variance calculated off index returns: The variance for the index calculated at each month’s end, based on the daily return data for the index in that month. Multiplied with 21 to get monthly frequency. Reported as equal-weight and value weight.

Denotation: $\text{Var-I}_{\text{(Index), (Weighting), (Time)}}$

Risk-free rate: The Euribor 1-month floating rate as the risk-free proxy for the Eurostoxx50 index and 1-month Swedish T-bill as a risk-free proxy or the OMXS30 index. The logarithmic version reported, in line with the assumption that returns are lognormally distributed and the logarithmic version of CAPM holds in line with Campbell & Viceira´s (2002)

Denotation: $\text{Rf}_{\text{(Index), (Time)}}$

Excess return: Defined as the logarithmic returns less the risk-free rate. in line with the assumption that returns are lognormally distributed and the logarithmic version of CAPM holds in line with Campbell & Viceira´s (2002) Reported for equal-weight, value-weight and the index return,

Denotation: $\text{Re}_{\text{(Index), (Weighting), (Time)}}$

6. Results

6.1 Variable properties

6.1.1 Eurostoxx50

Table 1 – Descriptive statistics for the value-weighted independent variables for the Eurostoxx50 index

	Observations	Mean	Min	Max	STD
AC$_{ES50, VW, t-1}$	233	.1589449	.0075092	.6052715	.1016279
AV$_{ES50, VW, t-1}$	233	.0099816	.0016743	.0752632	.0100431
VAR-M$_{ES50, VW, t-1}$	233	.0014398	.0001008	.0121075	.0016727
VAR-I$_{ES50, VW, t-1}$	233	.0015686	.0001666	.0145323	.0017485
Re$_{ES50, VW, t-1}$	232	.0026171	-.1531502	.1089615	.043247
Rf$_{ES50, t-1}$	232	.0018182	-.0001593	.0044657	.0013335

In comparison to the descriptive statistics reported by Wilson & Pollet (2008), the Eurostoxx50 index is significantly less correlated than the CRSP data set, which has a mean average correlation of rho = 0,237. Even though the study is conducted over a different time horizon and the results are not directly comparable, there is still a notably lower correlation. The different variance measures are not comparable, as Wilson & Pollet (2008) reports descriptive statistics with a quarterly frequency. As can be seen on the descriptive statistics during market downturns (appendix table 19), correlation increases during market downturn periods. A characteristic is in line with Longin and Solnik (2001) findings, who present evidence that correlation is driven by market trend. All other risk measures also demonstrate similar characteristics, indicating that all of the variables likely capture a portion of some form of risk, as they are increasing during market downturns, i.e. periods of negative and/or low excess return.

Table 2 – Correlation matrix for the value-weighted independent variables and the primary dependent variable, value-weighted excess return in period t for the Eurostoxx50 index

	Re$_{ES50, VW, t}$	**AC**$_{ES50, VW, t-1}$	**AV**$_{ES50, VW, t-1}$	**VAR-M** $_{ES50, VW, t-1}$	**VAR-I** $_{ES50, VW, t-1}$	**Re**$_{ES50, VW, t-1}$	**Rf**$_{ES50, t-1}$
Re$_{ES50, EW, t}$	1.0000						
AC$_{ES50, VW, t-1}$	-0.0831	1.0000					
AV$_{ES50, VW, t-1}$	-0.0745	-0.1382	1.0000				
VAR-M$_{ES50, VW, t-1}$	-0.1253	0.4104	0.7529	1.0000			
VAR-I$_{ES50, VW, t-1}$	-0.1365	0.3053	0.8320	0.9770	1.0000		
Re$_{ES50, VW, t-1}$	0.3022	-0.2135	-0.2805	-0.4234	-0.4506	1.0000	
Rf$_{ES50, t-1}$	-0.1905	-0.5704	0.4077	0.0601	0.1462	-0.1787	1.0000

The correlation matrix indicates that both the lagged constituent correlation and variance correlates negatively with the future excess return. A positive coefficient is a requisite for the risk-reward trade-off to hold, as more risk should correspond to higher expected excess returns in the future. The correlation matrix is indicative that holding excess risk in period *t-1* corresponds to lower returns in period *t*, echoing Campbell (1987) among others, who claim a negative relation with variance and expected excess return. Constituent variance is more positively correlated with index variance than the constituent correlation, regardless which calculation methodology is applied. Furthermore, constituent correlation is negatively correlated with constituent variance, contrary to Wilson & Pollet's (2008) findings, as well as the OMXS30 data reported below.

6.1.2 OMXS30

Table 3 – Descriptive statistics for the value-weighted independent variables for the OMXS30 index for the entire time period

	Observations	Mean	Min	Max	STD
$\mathbf{AC}_{\mathbf{OMX, VW, t-1}}$	233	.4002867	.0687882	.8091449	.1640511
$\mathbf{AV}_{\mathbf{OMX, VW, t-1}}$	233	.0099448	.0015719	.05863	.009421
$\mathbf{VAR\text{-}M}_{\mathbf{OMX, VW, t-1}}$	233	.0041769	.0002591	.0366307	.0051493
$\mathbf{VAR\text{-}I}_{\mathbf{OMX, VW, t-1}}$	233	.0049681	.0003673	.0406785	.0057739
$\mathbf{Re}_{\mathbf{OMX, VW, t-1}}$	232	.0017243	-.1725469	.1514077	.0601543
$\mathbf{Rf}_{\mathbf{OMX, t-1}}$	232	.0016576	0	.0038246	.0012587

The mean for constituent correlation is significantly higher for the OMXS30 index than the Eurostoxx50 index. This is likely due to the fact that OMXS30 is a national index, whereas the Eurostoxx50 index consists of stocks from all across the Eurozone. While these countries share the same currency and many of the blue-chip stocks constituting the index are global firms, national stock indices tend to commove to a greater extent. Other potential sources for differing results for the Eurostoxx50 include the fact that stocks are affected by different macroeconomic conditions and policy changes, as well as the OMXS30 being overweight financials and industrials. Constituent correlation, constituent variance and index variance all increase during market downturns (see appendix for comparison). Strengthening the theory that correlation increases as a result of market trend, Longin & Solnik (2001).

Table 4 – Correlation matrix for the value-weighted independent variables and the primary dependent variable, value-weighted excess return in period t for the OMXS30 index for the entire time period

	$Re_{OMX, VW, t}$	$AC_{OMX, VW, t-1}$	$AV_{OMX, VW, t-1}$	VAR-M $_{OMX, VW, t-1}$	VAR-I $_{OMX, VW, t-1}$	$Re_{OMX, VW, t-1}$	$Rf_{OMX, t-1}$
$Re_{OMX, EW, t}$	1.0000						
$AC_{OMX, VW, t-1}$	0.0274	1.0000					
$AV_{OMX, VW, t-1}$	-0.0757	0.1087	1.0000				
VAR-$M_{OMX, VW, t-1}$	-0.0481	0.4874	0.8623	1.0000			
VAR-$I_{OMX, VW, t-1}$	-0.0529	0.4033	0.9177	0.9711	1.0000		
$Re_{OMX, VW, t-1}$	0.1202	-0.2551	-0.2079	-0.2926	-0.2885	1.0000	
$Rf_{OMX, t-1}$	-0.1815	-0.1409	0.5994	0.4095	0.4543	-0.1730	1.0000

The correlation matrix contrary to the finding for the Eurostoxx50 data set, indicates that constituent variance and correlation are positively correlated with each other. As can be seen in the appendix, constituent correlation becomes significantly more correlated with future excess returns during market downturns. The results are indicative of a potential risk-reward trade-off, given that constituent correlation is positively correlated with future excess returns. Furthermore, the contemporaneous relationship between constituent correlation and index variance increases during market downturns. Possibly indicating that the constituent correlation multiple captures market shocks, as the correlation increase is simultaneous to an increase in average variance.

6.2 Index Variance Decomposition

As discussed in the literature overview, the variance calculated directly off the index returns for period *t* should be a function of the average correlation and average variance of the constituents. It is tested if the average value-weighted correlation explains a fraction of the index variance and that average correlation and average variance multiplied constitutes a proxy capturing almost the entire variance calculated off the index returns. To strengthen the results, this is tested for both the Eurostoxx50 index and the complementary dataset constituted by the OMXS30 index. OLS regressions with standard errors are reported for the regression. No qualitatively different results become apparent when a Newey-West t-statistic with four lags is reported (see Appendix).

6.2.1 Eurostoxx50 index variance

Table 5 reports an ordinary least square regression on the stock market index variance, regressed against different combinations of the lagged average correlation and average variance of the constituent stocks in that period for the Eurostoxx50 index.

Table 5 – Contemporaneous regressions on the index variance, measured through the value-weighted return in period t for the Eurostoxx50 index

VARIABLES	(1) $\text{VAR-I}_{ES50, VW, t}$	(2) $\text{VAR-I}_{ES50, VW, t}$	(3) $\text{VAR-I}_{ES50, VW, t}$	(4) $\text{VAR-I}_{ES50, VW, t}$
$AC_{ES50, VW, t}$	0.144***		0.155***	
	(22.46)		(36.83)	
$AV_{ES50, VW, t}$		0.005***	0.007***	
		(4.77)	(17.84)	
$\text{VAR-M}_{ES50, VW, t}$				1.021***
				(69.52)
Constant	0.000	0.001***	-0.001***	0.000***
	(1.51)	(3.80)	(-12.30)	(3.02)
Observations	234	234	234	234
R-squared	0.685	0.089	0.868	0.954

t-statistics in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Column 1 indicates that the value-weighted variance for all the stock constituents of the Eurostoxx50 index captures 68,5% of the variations in the index variance. As shown in column 2 the value-weighted average correlation for all the stock constituents captures 8,9% of the total variation in the index variance, a much smaller fraction than what the average variance for all the stock constituents captures. As the average variance and correlation are negatively correlated, the explanatory power is substantially increased by regressing the index variance on both the average variance and correlation for the stock constituents simultaneously. As shown by equation 17 the average correlation and average variance multiplied, should in theory comprise the index variance. Regressing the index variance on the theoretical proxy yields an R^2 – value of 95,4%. The coefficient is close to 1 and should in theory be equal to 1. A potential explanation for this discrepancy is a measurement error arising when calculating the average variance and correlation. Nonetheless, the average variance and correlation multiplied captures almost the entire variation of contemporaneous stock market variance. The average variance, average correlation and correlation multiplied with variance, remains statistically significant with a p-value of below 1% for all regressions. Empirical results indicate that index variance can effectively be decomposed contemporaneously into average constituent correlation and variance. The results from the Eurostoxx50 regression strengthens the theory that index variance can be decomposed into average constituent variance and correlation.

6.2.2 OMXS30 index variance

Table 6 – Contemporaneous regressions on the index variance, measured through the value-weighted return in period t for the OMXS30 index

VARIABLES	(1) VAR-$I_{OMX, VW, t}$	(2) VAR-$I_{OMX, VW, t}$	(3) VAR-$I_{OMX, VW, t}$	(4) VAR-$I_{OMX, VW, t}$
$AC_{OMX, VW, t}$	0.567***		0.544***	
	(37.08)		(55.04)	
$AV_{OMX, VW, t}$		0.014***	0.010***	
		(6.78)	(18.25)	
VAR-$M_{OMX, VW, t}$				1.092***
				(64.95)
Constant	-0.001***	-0.001	-0.005***	0.000***
	(-3.18)	(-0.84)	(-18.11)	(3.68)
Observations	234	234	234	234
R-squared	0.856	0.165	0.941	0.948

t-statistics in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

In table 6, a similar regression is performed, but with the complementary OMXS30 dataset. Column 1 indicates that average variance alone captures more than the average correlation, of the total index variance. However, the average value-weighted correlation based on the OMXS30 data set shows a significantly higher explanatory power of the variation in the index variance than what the respective variable does in the regression on the Eurostoxx50 dataset. As the average correlation and variance are positively correlated with each other, the linear regression including both variables have an increased explanatory power and an R^2-value of 94,1%, almost equivalent to the multiplicative model. As with the Eurostoxx50 dataset almost the entire variation in the index variance is captured by the multiplicative variable of variance and correlation. All variables remain statistically significant with a p-value of below 1%. The data is supportive that index variance can be decomposed into constituent variance and constituent correlation. Both regressions for the OMXS30 and Eurostoxx50 indicate that index variance can effectively be decomposed. The results gain external validity as the regression has been tested on two separate datasets with similar results. These findings seem unrelated to the fact that constituent correlation is negatively correlated with constituent variance for the Eurostoxx50 data set and vice versa for the OMXS30.

6.3 The Predictability of Average Correlation

Testing the forecasting abilities of average correlation as a market risk proxy, the explaining variables have been lagged with one month to see if changes in the average correlation amongst the constituents can predict increases or decreases in future excess monthly returns. Below in table 7 the results for this are presented, when using Eurostoxx50 as the underlying index.

Table 7 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns

VARIABLES	(1) $Re_{ES50, VW, t}$	(2) $Re_{ES50, VW, t}$	(3) $Re_{ES50, VW, t}$	(4) $Re_{ES50, t}^{*}$	(5) $Re_{ES50, VW, t}$	(6) $Re_{ES50, VW, t}$	(7) $Re_{ES50, VW, t}$
$AC_{ES50, VW, t-1}$	-0.034		-0.039	-0.025			-0.078*
	(-1.20)		(-1.40)	(-0.72)			(-1.66)
$AV_{ES50, VW, t-1}$		-0.345	-0.402	-0.341			0.395
		(-1.22)	(-1.41)	(-0.95)			(0.54)
$VAR\text{-}I_{ES50, VW, t-1}$					-3.390**		-0.241
					(-2.11)		(-0.05)
$VAR\text{-}M_{ES50, VW, t-1}$						-3.230*	
						(-1.92)	
$Re_{ES50, VW, t-1}$							0.233***
							(3.17)
$Rf_{ES50, t-1}$							-9.360***
							(-3.37)
Constant	0.008	0.006	0.013**	0.006	0.008**	0.007*	0.028**
	(1.50)	(1.50)	(2.03)	(0.79)	(2.08)	(1.93)	(2.58)
Observations	233	233	233	233	233	233	232
R-squared	0.006	0.006	0.015	0.005	0.019	0.016	0.135

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

The results are indicative that neither average correlation nor average variance are statistically significant predictors of excess returns in the subsequent period, regardless if regressed on the value-weighted return or the actual Eurostoxx50 return. Furthermore, coefficient sign is "wrong", in the sense that an intertemporal risk-reward trade-off would require a positive coefficient. The reason being that if risk is high in period *t*, investors require a greater premium in terms of higher expected return. If the risk-reward trade-off is to hold intertemporally the coefficient needs to be positive, i.e. holding more risk in period *t-1* rewards the investor with realized excess returns in period *t*. The aggregate stock market variance measured either through the variable calculated directly based on past returns for the index, or the multiplicative variable, are statistically significant predictors for a p<5% respectively a p<10%. The regressions capture c. 2% of return variation in the subsequent period. However, the effect captured in the regression is the opposite to what the risk-reward framework implies, as the coefficient is negative. These findings are at odds with Wilson & Pollet (2008). The implication is that holding the portfolio when the index variance is high, results in negative realized returns in the subsequent period. When controlling for the lagged dependent variable and the lagged risk-free rate, the market variance is not a significant predictor of returns. Including all variables in the regression, yields an R^2-value of 13,5%. The average correlation variable becomes statistically significant, however, this is likely a residual event from including the lagged return. The coefficient remains negative, indicating that the data does not support an intertemporal risk-reward trade-off for the full time series, where average correlation is a predictor of excess returns.

Table 8 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns

VARIABLES	**(1)** **$Re_{OMX, VW, t}$**	**(2)** **$Re_{OMX, VW, t}$**	**(3)** **$Re_{OMX, VW, t}$**	**(4)** **$Re_{OMX, t}^{*}$**	**(5)** **$Re_{OMX, VW, t}$**	**(6)** **$Re_{OMX, VW, t}$**	**(7)** **$Re_{OMX, VW, t}$**
$AC_{OMX, VW, t-1}$	0.012		0.015	0.022			0.004
	(0.49)		(0.60)	(0.95)			(0.10)
$AV_{OMX, VW, t-1}$		-0.354	-0.386	-0.198			0.238
		(-0.85)	(-0.91)	(-0.50)			(0.14)
$VAR\text{-}I_{OMX, VW, t-1}$					-0.337		0.323
					(-0.49)		(0.11)
$VAR\text{-}M_{OMX, VW, t-1}$						-0.295	
						(-0.38)	
$Re_{OMX, VW, t-1}$							0.105
							(1.50)
$Rf_{OMX, t-1}$							-9.395**
							(-2.28)
Constant	-0.003	0.005	-0.000	-0.005	0.003	0.003	0.011
	(-0.30)	(0.89)	(-0.04)	(-0.44)	(0.62)	(0.55)	(0.65)
Observations	233	233	233	233	233	233	232
R-squared	0.001	0.003	0.005	0.004	0.001	0.001	0.044

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

The OMXS30 exhibits slightly differing results to the Eurostoxx50 dataset. No variables indicate any statistically significant predictability for excess returns. Notable in comparison to the Eurostoxx50 dataset is the fact that the coefficient is positive, which it should be in theory under an efficient risk-reward trade-off. Revising the characteristics of the variables used in the regression for the respective indices, an apparent difference is that average correlation and average variance are correlated for OMXS30, but not for Eurostoxx50. When the regression is controlled for lagged excess return and the lagged risk-free rate, only the risk-free rate remains a significant predictor for excess returns for a p<5% probability, with an R^2 of 4,4%, significantly lower than the 13,5% for the respective regression on the Eurostoxx50 index. The results from the regressions on the OMXS30 index in conjunction with the results from Eurostoxx50 index, indicates that average correlation is not a predictor of excess returns in the subsequent period.

Results are not dependent on weighting procedure and equal-weighted regressions are reported in the appendix.

6.4 Average correlation as a predictor during market downturns

A final test is computed, to distinguish whether there is any significant discrepancy between the predictability of the decomposed risk proxies during certain market conditions in contrast to the entire data set. Relating back to Wilson & Savor (2014) and Longin & Solnik (2001) which studied the conditional relationship between risk and reward, the test aims to break out sub-periods during which there has been a market downturn or when GDP-growth has been negative on a quarterly basis.

Table 9 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns during market downturns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	$Re_{ES50, VW, t}$	$Re_{ES50, VW, t}$	$Re_{ES50, VW, t}$	$Re_{ES50, t}^{*}$	$Re_{ES50, VW, t}$	$Re_{ES50, VW, t}$	$Re_{ES50, VW, t}$
$AC_{ES50, VW, t-1}$	0.189*		0.175	0.155			0.077
	(1.79)		(1.58)	(1.22)			(0.47)
$AV_{ES50, VW, t-1}$		-0.533	-0.300	-0.467			1.176
		(-0.94)	(-0.52)	(-0.70)			(0.68)
$VAR\text{-}I_{ES50, VW, t-1}$					-2.124		-3.310
					(-0.66)		(-0.34)
$VAR\text{-}M_{ES50, VW, t-1}$						-1.081	
						(-0.31)	
$Re_{ES50, VW, t-1}$							0.148
							(0.87)
$Rf_{ES50, t-1}$							-20.834**
							(-2.49)
Constant	-0.043*	0.003	-0.035	-0.035	0.000	-0.003	0.013
	(-1.92)	(0.21)	(-1.30)	(-1.13)	(0.02)	(-0.22)	(0.33)
Observations	39	39	39	39	39	39	39
R-squared	0.080	0.023	0.087	0.067	0.012	0.003	0.298

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

The average correlation variable is a statistically significant predictor with a p-value of below 10%, and with an R^2 of 8%. When controlling for other variables, the average correlation variable loses its significance but retains the positive coefficient, for all regressions. The average variance variable has a negative coefficient when regressed alone on the future excess return, implying that high average variance, all else equal, penalizes investors with lower excess returns in the future.

During periods of market downturn only the risk-free rate retains significance as a predictor, when all variables are included in the regression. The R^2 more than doubles, indicating that the complete model is a better predictor during market downturns. An increase in the average constituent variance, without an equivalent increase in correlation, is likely indicative of idiosyncratic risk factors, in accordance with Wilson & Pollet (2008), of which investors are not entitled to a risk premium for. The different measures of index variance when regressed alone, both retain the “wrong” coefficient to be indicative of a risk-reward trade-off as discussed by Wilson & Pollet (2008). Providing some support that the decomposition of index variance provides additional explanation to predictability and market dynamics. For the control definition of market downturn (see appendix), average correlation does not demonstrate the necessary properties nor any significance as a predictor of excess returns. The results, while not being conclusive and statistically robust for lower p-values, are indicative of some relationship between the lagged average correlation and future excess returns, conditional on the time period chosen to define market downturns. Echoing important insights from Roll (1998), that the efficiency likely is dependent on the time period, data set and market proxy chosen.

Table 10 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns during market downturns

VARIABLES	**(1)** $Re_{OMX, VW, t}$	**(2)** $Re_{OMX, VW, t}$	**(3)** $Re_{OMX, VW, t}$	**(4)** $Re_{OMX, t}^{*}$	**(5)** $Re_{OMX, VW, t}$	**(6)** $Re_{OMX, VW, t}$	**(7)** $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	0.114		0.165*	0.115			0.154
	(1.30)		(1.79)	(1.30)			(1.16)
$AV_{OMX, VW, t-1}$		-0.945	-1.655	-0.725			6.949
		(-0.89)	(-1.52)	(-0.70)			(1.09)
$VAR\text{-}I_{OMX, VW, t-1}$					-0.683		-8.483
					(-0.49)		(-0.97)
$VAR\text{-}M_{OMX, VW, t-1}$						-0.738	
						(-0.46)	
$Re_{OMX, VW, t-1}$							-0.166
							(-0.88)
$Rf_{OMX, t-1}$							-52.869***
							(-4.02)
Constant	-0.076	-0.005	-0.079*	-0.068	-0.012	-0.013	-0.011
	(-1.64)	(-0.25)	(-1.73)	(-1.56)	(-0.67)	(-0.69)	(-0.15)
Observations	29	29	29	29	29	29	29
R-squared	0.059	0.029	0.135	0.063	0.009	0.008	0.494

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

For the OMXS30 index the same effect is captured as with the regressions for the Eurostoxx50. Notably, market downturn as defined by negative seasonally adjusted GDP growth, includes fewer periods than for the Eurostoxx50 index. While the fact that the periods denoted as market downturns differ, could be problematic from a comparability point of view, this is motivated by the fact that the same criterion was applied to single out these periods. Another caveat is that N<30, the normal threshold for when N is considered large. However, this threshold is somewhat arbitrary and considering the fact that the same selection criteria has been applied, conclusions can still be made based on the finding, albeit with some more caution.

The effect captured is similar to that for the Eurostoxx50 dataset. Average constituent correlation becomes a more significant predictor of excess returns and the R^2-value improves for all combinations of the regressions. The average correlation is significant for a p-value of below 10%, when regressed together with the average variance. The index variance does not have the right properties of the coefficient nor is a statistically significant predictor of excess returns. The findings are consistent with the findings for the Eurostoxx50 index, during market downturns as defined by negative GDP growth.

In summary, while no definite conclusions can be drawn concerning the predictability of average correlation, the data seems to capture an effect where predictability increases during market downturns for both data sets. The results seem conditional on the definition of market downturns and during the more generalized definition of a crisis period (see appendix), no predictability nor indicative variable properties are found.

6.5 Robustness checks

A number of robustness checks have been employed to solidify the results. To increase external validity and avoid risks of data snooping, the results of one complementary data set have been reported. The Eurostoxx50 index, is a supranational index consisting of the 50-largest most liquid blue chips stocks in the Eurozone area. Echoing Bali, Cakici, Yan & Zang (2005), the upside with such an index is that equal-weighted measurements can be used, without running the risk of misleading metrics due to distortion to the average variance and correlation from liquidity premiums as was the case in Goyal & Santa-Clara (2001), which is the case when a larger[5] index, e.g. S&P500 is used and more illiquid stocks are included. Contrary to the dataset

[5] In terms of N, the number of constituents included in the index.

used in Wilson & Pollet (2008) study, the Eurostoxx50 is not a national index, and hence affected by different macroeconomic decisions and country specific factors. This is another reason for including the OMX30 index, to make sure that differing results are not mainly the consequence of not using a national index.

Autocorrelation is a common phenomenon occurring in time series data. It is often argued that autocorrelation is problematic when studying the stock market, especially when looking at daily returns. Consider a sharp decline in stock price, certain automatic risk management systems are triggered as price decreases and the trading systems start getting rid of their long positions. As such the initial drop causes more volatility, as more trades are executed in the market and prices fluctuate. As such both variance and returns are likely to exhibit tendencies of autocorrelation.

To test for autocorrelation a Barlett-correlogram is plotted in the appendix. The graph is indicative for autocorrelation for the first and fourth lag for the excess value-weighted return in the Eurostoxx50 index and for the third lag for the value-weighted returns for the OMXS30 index. As such Newey-West t-statistics is used in the regression, a common methodology used to try to overcome the autocorrelation. No qualitatively different results are found with regards to the predictability of the risk capturing variables when a Newey-West t-statistic is used. The market downturn periods are constituted by different sub-time series collapsed into one. Due to dates not being regularly spaced, autocorrelation is not considered a significant issue.

7. Discussion

Revisiting Driessen et al.’s (2009) model of market risk premium (equation 5), the results indicate the risk proxy can be decomposed, where index variance contemporaneously can be explained by the average correlation and average variance of the constituents. In contrast to Driessen et al. (2009) the data suggests that average individual stock variance and correlation are negatively correlated with each other for the Eurostoxx50 index. Potentially indicating that the majority of the risk that is captured in the decomposition relates to idiosyncratic deviations and subsequently the majority of the risk for the index is explained by this. When average correlation is high, average variance tends to be low indicating that correlation only is high in the absence of idiosyncratic shocks. Average variance is relatively more correlated with the stock market index variance than the average correlation is. As the lagged stock market variance is negatively correlated with future excess returns, it indicates that the risk captured by the stock market variance primarily contains diversifiable risk and not market risk where the investor requires a risk premium for holding the asset. As no intertemporal risk-reward trade-off can be found in the data for the stock market variance, results are inconsistent with Wilson & Pollet (2008).

Wilson & Pollet (2008), highlight the Roll Critique as an important counter to the argument that average correlation has significance as a part of the risk factor in the mean-variance trade off. Applying the Roll Critique (Roll, 1976), this would imply going beyond criticizing the usage of a risk proxy such as average correlation, and argue that changes in stock market variance may only be weakly related to changes in aggregate risk, and subsequently in excess returns. This is of importance, as the Roll Critique would criticize both the CAPM (and the efficient market) and the argument that return on aggregate wealth is not directly observable. Most problematic for this paper when applying the Roll Critique would be that the linear relationship between risk and reward would follow the market portfolio’s efficiency, and are not independently testable. Furthermore, this risk-reward relationship is not reliably testable without the exact composition of the true market portfolio instead of a proxy. Our indices have N (where N is the number of constituent stocks) less than Wilson & Pollet´s study (which uses the S&P500). Even if N were greater, capturing aggregate market wealth is complex, as the aggregate market portfolio would include all investment opportunities on the efficient frontier, including other asset classes and non-listed assets. This is an additional obstacle when testing the efficient market.

Capturing the market portfolio by using proxies is difficult in several ways, amongst other things as the market proxy may be mean-variant efficient even if the true market portfolio is not. Furthermore, when in this case a proxy index is constituted, these indices will reasonably be very highly correlated with each other (due to systematic risk) as well as with the true market portfolio, whether or not these proxies or the true market portfolio are mean-variance efficient. This high correlation between proxies make it seem as the indices' constituents are irrelevant as long as N is large and correlation with the true market is high. In fact, the results from different compositions can vary significantly when testing the mean-variance relationship, as the results from this paper would indicate. These differences can amongst other things be attributed differences in idiosyncratic risk, average correlation and variance amongst the individual constituents, and liquidity premiums.

This would imply that the dataset used as a proxy for the market portfolio is rather important, as results vary depending on what proxy is used. The previous studies on this relatively narrow topic have looked at the S&P, both S&P 500 and 100, and the differing results may very well be due to the difference in the market proxy's composition, where some are efficient and some are not. Whether the true market is efficient in this case is unknown and thus the conclusion which can be made is that the significance of average correlation as a predicting variable will depend on the accuracy of the proxy for the market, in line with the Roll Critique.

Moving from the CAPM and the efficient market, let it be assumed that CAPM does hold and the market proxies used are efficient. This allows a closer look at the proxy for risk, which as the results indicated, can be decomposed into average constituent variance and correlation. In line with Wilson & Pollet (2008) we find a negative relationship between lagged average variance and stock market returns, which also would be in line with the findings of Bali, Cakici, Yan & Zang (2005). Contemporaneously average correlation and average variance are negatively correlated with excess returns. These findings indicate that correlation has a contemporaneous relationship with excess returns similar to the one illustrated by the more sophisticated methods employed by Longin & Solnik (2001). The contemporaneous findings are consistent with Wilson & Pollet (2008), however no predictability is discovered for the average correlation and variance variable in the predictive regressions.

If we take the opposite approach and side with the Roll Critique, let it be assumed that market proxies are efficient at some times and inefficient at others. This would also relate back to Wilson & Savor (2014) and Jagannathan & Wang (1996), which show that stock market beta is a determinant of risk premium and relates to future excess returns, depending on market conditions. This would imply that even if the stock market on average is not efficient, and beta does not have forecasting ability of excess return, there might be certain market conditions where it is efficient. Assuming this is the case, and building on Longin & Solnik's (2001) study on average correlation increasing in market downturns, this has been tested in the paper.

As seen in the results, periods with negative GDP growth have been broken out from the data, showing increasing significance in the forecasting ability of average correlation. The underlying theory for why this was tested was from Wilson & Savor's (2014) study which concluded that the relationship between risk and return was strongly positive during certain market conditions when investors demand higher return to hold higher-beta assets. Due to the negative skewness in the Eurostoxx50 data set, and based on the results from Longin & Solnik (2001) that average correlation increases in market downturns, these tendencies should have become more apparent if any pattern exists during market downturns. In line with these previous studies, the forecasting ability of average correlation increases during these periods of market downturns.

There are several possible reasons for this, amongst others that in the times when investors require higher returns to hold high-beta assets, this changes the risk-reward dynamic in the market. When average variance increases together with average correlation, this increases the systematic market risk, and as the results indicate, a tendency in which average correlation and average variance can predict future excess returns is distinguished.

When the controlling sub-periods are broken out, and the three recent financial crises are used as periods of market downturn instead, the significance diminishes. This might partly be explained by the fact that the control periods have too generalized definitions of market downturns, which do not correspond to the data set and thus constitute a poor proxy for market downturn.

Another potential reason may be the relative increases in average variance compared to average correlation. In contrast to the previous result of negative GDP growth being examined as a market downturn, this change in risk may be attributed to other risk aspects than systematic risk. In other words, when average variance increases more than average correlation, so that the increase in correlation during market downturns (in accordance with Longin & Solnik (2001)) would be reflected in the change in aggregate idiosyncratic risk. Thus affecting the dynamic in the market risk-reward trade-off, but not necessarily result in an efficient market in which CAPM holds.

This distinction of risk gains importance for the question if lagged average stock correlation is a predictor of future excess returns during market downturns. When changes in market conditions cause both average correlation and variance to increase, it is indicative of systematic risk. This risk increase correlates positively with increases in future excess returns, in line with a risk-reward relationship conditional on market trends, as well as with Wilson & Pollet (2008) distinction of risk in relation to returns.

8. Conclusion

This paper examines (i) the contemporaneous index variance and whether it can be decomposed into constituent variance and correlation, (ii) if lagged average constituent stock correlation is a predictor of future excess returns, (iii) if lagged average constituent stock correlation is a predictor of future excess returns during market downturns.

In accordance with the conclusions of Wilson & Pollet (2008) and that of Driessen, Maenhout and Vilkov (2009), the results confirmed that risk can be decomposed contemporaneously into average constituent correlation and average variance. When examining if average correlation is a predictor of future excess returns, a forecasting relationship is only found during market downturns, indicative of a conditional risk-reward trade-off. This is explained partly by the (i) Roll Critique, as different market proxies cause deviating results depending on the constituents, (ii) distinguishing changes in idiosyncratic risk from systematic risk as the risk proxy´s components vary over time (iii) the conditionality of market efficiency.

8.2 Further Research

As it has been concluded that the Roll critique is of importance when studying the role of average correlation, where results differ depending on the constituents of the market proxy, extending this study with a different sample would be of interest. All factors which could help improve the accuracy of the risk proxy and the risk-return relationship could be examined further. For example expanding to a multifactor model in the style of Fama & French (1996), and tweak factors which disrupt the models forecasting ability, for example adjusting for size to reduce liquidity premiums, or to include time-varying discount rates based on Cochrane (2011).

These potential adjustments would also include testing indices of national and international constituents, together with larger and smaller market proxies (defined by N), to see which proxies come close to an efficient market. Together with changes in the dataset, a method change would also be of interest. Ghysels, Santa-Clara & Valkanov (2004) find a significant forecasting relationship between risk and returns in the ICAPM by using a Mixed Data Sampling approach. This same approach is mentioned in Wilson & Pollet (2008), and would be a relevant expansion of the study. Using MIDAS, it would be highly relevant to also re-test the data samples broken out as market downturns, i.e. the periods where tendencies of conditional risk-reward relationship is found. Despite the usage of a different data set, in comparison to Wilson & Pollet (2008), the results in this paper are relatively less significant, and using a MIDAS approach could potentially increase significance as more data points are used.

On the other hand, studies such as of Ghysels, Plazzi & Valkanov (2013), show that using MIDAS, data periods which would be identified as financial crisis and “flight to safety” periods, show no significant positive or negative risk-reward trade-off. If this is a result from changing the data sample or method is unknown and would be of interest to investigate further.

Furthermore, relating back to Driessen, Maenhout & Vilkov (2009) and correlation risk premia, it might also be of interest to create a trading strategy using correlation as a forecasting variable, and apply this in option trading strategy. In the light of Jegadeesh & Titman (1993) which find that short-term returns tend to continue in a momentum trend, adding a momentum component to buy indices or baskets when correlation is increasing and to sell once correlation has seized to increase, would be one potential take, assuming the indices included have features of an efficient market.

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Appendix

A. Changes in Data Set

Table 11 – Manually assigned market capitalization to the constituent stocks where no market capitalization was available in the Eurostoxx50 Index

Stock	Entry date	Assigned market cap	Exit date
HVMG	20-Sep-1999	6093 mEUR	17-Sep-1999
NPM	11-Sep-1998	5194 mEUR	18-Jul-2005
Rhone	11-Sep-1998	5194 mEUR	27-Jul-2004
Edition Canal	11-Feb-2000	6526 mEUR	08-Dec-2000
RLX	11-Sep-1998	5194 mEUR	19-Sep-2003
Suez	20-Sep-1999	6093 mEUR	21-Jul-2008

A.1 Changes in EuroStoxx50

Constituent changes for the Eurostoxx 50 from oct-1998 to apr-2018. Changes in constituents or ticker changes have been accounted for in the daily returns data set. When a constituent has left the index, the return data is replaced so that the entrant starts trading on the switching date (t), and the exiting constituent has its final trading day (t-1) in Eurostoxx 50. A (+) indicates that the company has been added to the index and a (-) indicates that the company has been removed from the index.

Table 12 – All constituent changes in the Eurostoxx50 index from oct-1998 to apr-2008

	Company	Ticker	Date
+	Adidas	ADSGn.DE	19-Sep-2016
+	Ahold Delhaize	AD.AS	19-Sep-2016
-	Carrefour	CARR.PA	19-Sep-2016
+	CRH	CRH.I	19-Sep-2016
-	Generali	GASI.MI	19-Sep-2016
-	UniCredit	CRDI.MI	19-Sep-2016
-	Uniper	UN01.DE	13-Sep-2016
+	Uniper	UN01.DE	12-Sep-2016
+	Fresenius	FREG.DE	21-Sep-2015
-	Repsol	REP.MC	21-Sep-2015
-	RWE	RWEG.DE	21-Sep-2015
+	Safran	SAF.PA	21-Sep-2015
-	CRH	CRH.I	22-Sep-2014

+	Nokia	NOKIA.HE	22-Sep-2014
-	ArcelorMitta	MT.AS	23-Sep-2013
+	Deutsche Post	DPWGn.DE	23-Sep-2013
-	Osram Licht	OSRn.DE	09-Jul-2013
+	Airbus NL	AIR.PA	18-Mar-2013
-	Nokia	NOKIA.HE	18-Mar-2013
+	ASML Holding	ASML.AS	18-Jun-2012
-	Deutsche Boerse	DB1Gn.DE	18-Jun-2012
+	Essilor	ESSI.PA	18-Jun-2012
-	Telecom IT	TLIT.MI	18-Jun-2012
+	Deutsche Boerse	DB1Gn.DE	08-Feb-2012
-	Deutsche Boerse	DB1Gne.DE^B12 (expired)	08-Feb-2012
-	Alstom	ALSO.PA	19-Sep-2011
-	Credit Agricole	CAGR.PA	19-Sep-2011
+	Inditex	ITX.MC	19-Sep-2011
+	Volkswagen	VOWG_p.DE	19-Sep-2011
-	Deutsche Boerse	DB1Gn.DE	20-Jul-2011
+	Deutsche Boerse	DB1Gne.DE^B12 (expired)	20-Jul-2011
-	DIA	DIDA.MC	06-Jul-2011
+	DIA	DIDA.MC	05-Jul-2011
-	Aperam	APAM.AS	01-Feb-2011
-	Aegon	AEGN.AS	20-Sep-2010
+	BMW	BMWG.DE	20-Sep-2010
+	Unibail Rodamco	UNBP.AS	08-Feb-2010
-	Volkswagen	VOWG.DE	08-Feb-2010
+	AB Inbev	ABI.BR	21-Sep-2009
-	Ageas	AGES.BR	21-Sep-2009
+	CRH	CRH.I	21-Sep-2009
-	Renault	RENA.PA	21-Sep-2009
-	Alcatel Lucent	ALUA.PA^K16 (expired)	22-Sep-2008
+	Alstom	ALSO.PA	22-Sep-2008
+	Engie	ENGIE.PA	22-Jul-2008
-	Suez eniivi	LYOE.PA^F10 (expired)	22-Jul-2008
+	Deutsche Boerse	DB1Gn.DE	15-Oct-2007
-	RBS Hldg	AAH.AS^D08 (expired)	15-Oct-2007

-	Endesa	ELE.MC	10-Oct-2007
+	Volkswagen	VOWG.DE	10-Oct-2007
-	Ahold Delhaize	AD.AS	24-Sep-2007
-	AIB Grou	AIBG.I	24-Sep-2007
+	ArcelorMitta	MT.AS	24-Sep-2007
-	Lafarge	LAFP.PA^J15 (expired)	24-Sep-2007
+	Schneider	SCHN.PA	24-Sep-2007
+	Vinci	SGEF.PA	24-Sep-2007
+	Intesa Sanpaolo	ISP.MI	02-Jan-2007
-	Sanpaolo IM	SPI.MI^A07 (expired)	02-Jan-2007
+	Renault	RENA.PA	20-Jul-2005
-	Shell	RDSa.AS	20-Jul-2005
-	Koninklijke NPM	RD.AS^A06 (expired)	19-Jul-2005
+	AIB Grou	AIBG.I	30-Jun-2005
-	Telecom Mobile	TIM.MI^F05 (expired)	30-Jun-2005
+	Credit Agricole	CAGR.PA	20-Sep-2004
-	Volkswagen	VOWG.DE	20-Sep-2004
-	Rhone Poulenc	AVEP.PA^J05 (expired)	28-Jul-2004
+	SAP SE	SAPG.DE	28-Jul-2004
+	Iberdrola	IBE.MC	22-Sep-2003
-	UniCredit	HVMG.DE^I08 (expired)	22-Sep-2003
+	Telecom IT	TLIT.MI	04-Aug-2003
-	Telecom It old	TIT.MI^H03 (expired)	04-Aug-2003
-	Kering	PRTP.PA	23-Sep-2002
+	Lafarge	LAFP.PA^J15 (expired)	23-Sep-2002
-	Ageas	AGES.BR	17-Dec-2001
+	Ageas	AGES.BR	17-Dec-2001
+	Cie Saint Gobain	SGOB.PA	24-Sep-2001
-	KPN	KPN.AS	24-Sep-2001
-	Dresdner Bank	DRSDn.DE^G02 (expired)	23-Jul-2001
+	Telecom Mobile	TIM.MI^F05 (expired)	23-Jul-2001
-	Edition Canal	CNLP.PA^I15 (expired)	11-Dec-2000
+	Volkswagen	VOWG.DE	11-Dec-2000
-	Ceconomy	CECG.DE	18-Sep-2000
+	Danone	DANO.PA	18-Sep-2000

-	Electrabel	ELCBt.BR^G07 (expired)	18-Sep-2000
+	Sanpaolo IM	SPI.MI^A07 (expired)	18-Sep-2000
-	Cie Saint Gobain	SGOB.PA	20-Mar-2000
+	Enel	ENEI.MI	20-Mar-2000
+	Edition Canal	CNLP.PA^I15 (expired)	14-Feb-2000
-	Vodafone	VDFGn.DE^H02 (expired)	14-Feb-2000
+	BNP Paribas	BNPP.PA	01-Nov-1999
-	Elf Aquitaine	ELFP.PA^D10 (expired)	01-Nov-1999
+	Kering	PRTP.PA	01-Nov-1999
-	Paribas SA	PARI.PA^A00 (expired)	01-Nov-1999
-	AIB Grou	AIBG.I	20-Sep-1999
-	Akzo Nobel	AKZO.AS	20-Sep-1999
+	Banco Santander	SAN.MC	20-Sep-1999
+	BASF SE	BASFn.DE	20-Sep-1999
+	Dresdner Bank	DRSDn.DE^G02 (expired)	20-Sep-1999
-	Fiat Chrysler	FCHA.MI	20-Sep-1999
-	Lufthansa	LHAG.DE	20-Sep-1999
+	Munich Re Group	MUVGn.DE	20-Sep-1999
-	Pharol	PHRA.LS	20-Sep-1999
-	Rlx	RELN.AS	20-Sep-1999
+	Sanofi FR	SASY.PA	20-Sep-1999
-	Schneider	SCHN.PA	20-Sep-1999
+	Suez eniivi	LYOE.PA^F10 (expired)	20-Sep-1999
+	UniCredit	HVMG.DE^I08 (expired)	20-Sep-1999
+	Total	TOTF.PA	16-Jun-1999
-	Total PR	PETBt.BR^L00 (expired)	16-Jun-1999
-	Daimler	DAIGa.F^L98 (expired)	12-Nov-1998
+	Daimler	DAIGn.F	12-Nov-1998
+	Daimler	DAIGa.F^L98 (expired)	26-Oct-1998
-	Daimler-Benz AG	DAIG.F^L98 (expired)	26-Oct-1998
+	Aegon	AEGN.AS	12-Aug-1998
+	Ageas	AGES.BR	12-Aug-1998
+	Ahold Delhaize	AD.AS	12-Aug-1998
+	AIB Grou	AIBG.I	12-Aug-1998
+	Air Liquide	AIRP.PA	12-Aug-1998

+	Akzo Nobel	AKZO.AS	12-Aug-1998
+	Alcatel Lucent	ALUA.PA^K16 (expired)	12-Aug-1998
+	Allianz	ALVG.F	12-Aug-1998
+	Axa SA	AXAF.PA	12-Aug-1998
+	Bayer	BAYGn.F	12-Aug-1998
+	BBVA	BBVA.MC	12-Aug-1998
+	Carrefour	CARR.PA	12-Aug-1998
+	Ceconomy	CECG.F	12-Aug-1998
+	Cie Saint Gobain	SGOB.PA	12-Aug-1998
+	Daimler-Benz AG	DAIG.F^L98 (expired)	12-Aug-1998
+	Deutsche Bank	DBKGn.F	12-Aug-1998
+	Deutsche Telekom	DTEGn.F	12-Aug-1998
+	E.ON	EONGn.F	12-Aug-1998
+	Electrabel	ELCBt.BR^G07 (expired)	12-Aug-1998
+	Elf Aquitaine	ELFP.PA^D10 (expired)	12-Aug-1998
+	Endesa	ELE.MC	12-Aug-1998
+	Eni	ENI.MI	12-Aug-1998
+	Fiat Chrysler	FCHA.MI	12-Aug-1998
+	Generali	GASI.MI	12-Aug-1998
+	ING Groep	INGA.AS	12-Aug-1998
+	Koninklijke NPM	RD.AS^A06 (expired)	12-Aug-1998
+	KPN	KPN.AS	12-Aug-1998
+	L'Oreal	OREP.PA	12-Aug-1998
+	Lufthansa	LHAG.F	12-Aug-1998
+	LVMH	LVMH.PA	12-Aug-1998
+	Nokia	NOKIA.HE	12-Aug-1998
+	Orange	ORAN.PA	12-Aug-1998
+	Paribas SA	PARI.PA^A00 (expired)	12-Aug-1998
+	Pharol	PHRA.LS	12-Aug-1998
+	Philips	PHG.AS	12-Aug-1998
+	RBS Hldg	AAH.AS^D08 (expired)	12-Aug-1998
+	Repsol	REP.MC	12-Aug-1998
+	Rhone Poulenc	AVEP.PA^J05 (expired)	12-Aug-1998
+	Rlx	RELN.AS	12-Aug-1998
+	RWE	RWEG.F	12-Aug-1998

+	Schneider	SCHN.PA	12-Aug-1998
+	Siemens	SIEGn.F	12-Aug-1998
+	Societe Generale	SOGN.PA	12-Aug-1998
+	Telecom It old	TIT.MI^H03 (expired)	12-Aug-1998
+	Telefonica	TEF.MC	12-Aug-1998
+	Total PR	PETBt.BR^L00 (expired)	12-Aug-1998
+	UniCredit	CRDI.MI	12-Aug-1998
+	Unilever	UNc.AS	12-Aug-1998
+	Vivendi	VIV.PA	12-Aug-1998
+	Vodafone	VDFGn.F^H02 (expired)	12-Aug-1998

A.2 Changes in OMXS30

Constituent changes for the OMXS30 from sep-1996 to apr-2018. Changes in constituents or ticker changes have been accounted for in the daily returns data set. When a constituent has left the index, the return data is replaced so that the entrant starts trading on the switching date (t), and the exiting constituent has its final trading day (t-1) in OMXS30. A (+) indicates that the company has been added to the index and a (-) indicates that the company has been removed from the index.

Table 13 – All constituent changes in the Eurostoxx50 index from sep-1996 to apr-2008

	Company	**Ticker**	**Date**
-	LundinPetroleum	LUPE.ST	02-Jan-2018
+	Essity	ESSITYb.ST	12-Jun-2017
+	Autoliv	ALIVsdb.ST	02-Jan-2017
-	Nokia	NOKIA.ST	02-Jan-2017
+	FPC	FINGb.ST	04-Jan-2016
-	Modern Times	MTGb.ST	04-Jan-2016
+	Kinnevik	KINVb.ST	01-Jul-2014
-	Scania	SCVb.ST^F14 (expired)	16-May-2014
-	Qliro Group	QLRO.ST	16-Dec-2010
-	Eniro	ENRO.ST	01-Jul-2009
+	Getinge	GETIb.ST	01-Jul-2009
+	Modern Times	MTGb.ST	01-Jul-2009
-	Vostok Gas	VGASsdb.ST^A09 (expired)	05-Jan-2009
-	Autoliv	ALIVsdb.ST	10-Dec-2008
+	LundinPetroleum	LUPE.ST	10-Dec-2008
-	LundinPetroleum	LUPE.ST	09-Dec-2008
-	Autoliv	ALIVsdb.ST	03-Jan-2008

+	LundinPetroleum	LUPE.ST	03-Jan-2008
+	SSAB	SSABa.ST	02-Jul-2007
-	Stora Enso	STEr.ST	02-Jul-2007
-	Nokia	NOKIsdb.ST^E07 (expired)	04-Jun-2007
+	Nokia	NOKIA.ST	04-Jun-2007
-	Holmen	HOLMb.ST	02-Jan-2007
+	Scania	SCVb.ST^F14 (expired)	02-Jan-2007
+	Boliden	BOL.ST	03-Jul-2006
-	Fabege	FABG.ST	03-Jul-2006
-	Old Mutual	OLDM.ST	03-Jul-2006
+	Vostok Gas	VGASsdb.ST^A09 (expired)	03-Jul-2006
-	FAB Skandia	SDIA.ST^F06 (expired)	15-Mar-2006
+	Fabege	FABG.ST	01-Nov-2004
-	Fabege Fastighet	FABGb.ST^A05 (expired)	01-Nov-2004
+	Nokia	NOKIsdb.ST^E07 (expired)	21-Jul-2003
+	Fabege Fastighet	FABGb.ST^A05 (expired)	01-Jul-2003
-	Nokia	NOKIsdb.ST^E07 (expired)	01-Apr-2003
-	Telenor Sverige	EURO.ST^D03 (expired)	05-Mar-2003
+	Alfa Laval AB	ALFA.ST	02-Jan-2003
-	CGI IT konsulter	WMb.ST^K06 (expired)	02-Jan-2003
-	Pharmacia	PHA.ST^D03 (expired)	02-Jan-2003
+	Swedish Match	SWMA.ST	02-Jan-2003
+	Eniro	ENRO.ST	02-Jul-2001
-	LB Icon	ICON.ST^G06 (expired)	02-Jul-2001
-	LBi Intl	LBI.ST^G10 (expired)	02-Jul-2001
+	Telenor Sverige	EURO.ST^D03 (expired)	02-Jul-2001
+	Assa Abloy	ASSAb.ST	02-Jan-2001
-	Kinnevik Ind	KINVb.ST^G04 (expired)	02-Jan-2001
-	Trelleborg	TRELb.ST	02-Jan-2001
+	LBi Intl	LBI.ST^G10 (expired)	03-Jul-2000
+	Telia Company	TELIA.ST	15-Jun-2000
-	Sandvik	SANDb.ST^E00 (expired)	10-May-2000
+	CGI IT konsulter	WMb.ST^K06 (expired)	01-Jan-2000
+	LB Icon	ICON.ST^G06 (expired)	01-Jan-2000
-	Scania	SCVb.ST^F14 (expired)	01-Jan-2000
+	Securitas	SECUb.ST	01-Jan-2000
-	Stora Enso	STEa.ST	01-Jan-2000
-	AGA	AGAb.ST^D00 (expired)	18-Oct-1999
+	Tele2	TEL2b.ST	02-Jul-1999
+	ABB	ABB.ST	23-Jun-1999
-	ABB AB	ABBPa.ST^G99 (expired)	23-Jun-1999
-	ABB AB	ABBPb.ST^G99 (expired)	23-Jun-1999
+	AstraZeneca	AZN.ST	07-Apr-1999
-	AstrZeneca	ASTRb.ST^D99 (expired)	06-Apr-1999

-	AstrZeneca	ASTRa.ST^D99 (expired)	06-Apr-1999
+	Stora Enso	STEa.ST	04-Jan-1999
+	Stora Enso	STEr.ST	04-Jan-1999
-	Stora Kopparberg	STORa.ST^B99 (expired)	30-Dec-1998
-	Avesta Sheffield	AVES.ST^B01 (expired)	23-Jun-1998
+	Nordea Bank	NDA.ST	23-Jun-1998
+	Autoliv	ALIVsdb.ST	22-Dec-1997
-	Stora Kopparberg	STORb.ST^A99 (expired)	22-Dec-1997
-	Investr	INVEa.ST	01-Jul-1997
+	Nokia	NOKIsdb.ST^E07 (expired)	01-Jul-1997
+	Scania	SCVb.ST^F14 (expired)	01-Jul-1997
-	Autoliv AB	ALIV.ST^E97 (expired)	12-May-1997
+	ABB AB	ABBPb.ST^G99 (expired)	24-Jun-1996
+	ABB AB	ABBPa.ST^G99 (expired)	24-Jun-1996
+	AGA	AGAb.ST^D00 (expired)	24-Jun-1996
+	AstrZeneca	ASTRb.ST^D99 (expired)	24-Jun-1996
+	AstrZeneca	ASTRa.ST^D99 (expired)	24-Jun-1996
+	Atlas Copco	ATCOb.ST	24-Jun-1996
+	Atlas Copco	ATCOa.ST	24-Jun-1996
+	Autoliv AB	ALIV.ST^E97 (expired)	24-Jun-1996
+	Avesta Sheffield	AVES.ST^B01 (expired)	24-Jun-1996
+	Cellulosa SCA	SCAb.ST	24-Jun-1996
+	Electrolux	ELUXb.ST	24-Jun-1996
+	Ericsson	ERICb.ST	24-Jun-1996
+	FAB Skandia	SDIA.ST^F06 (expired)	24-Jun-1996
+	Handelsbanken	SHBa.ST	24-Jun-1996
+	Hennes & Mauritz	HMb.ST	24-Jun-1996
+	Holmen	HOLMb.ST	24-Jun-1996
+	Investr	INVEa.ST	24-Jun-1996
+	Investr	INVEb.ST	24-Jun-1996
+	Kinnevik Ind	KINVb.ST^G04 (expired)	24-Jun-1996
+	Pharmacia	PHA.ST^D03 (expired)	24-Jun-1996
+	Sandvik	SAND.ST	24-Jun-1996
+	Sandvik	SANDb.ST^E00 (expired)	24-Jun-1996
+	SEB	SEBa.ST	24-Jun-1996
+	Skanska AB	SKAb.ST	24-Jun-1996
+	SKF	SKFb.ST	24-Jun-1996
+	Stora Kopparberg	STORa.ST^B99 (expired)	24-Jun-1996
+	Stora Kopparberg	STORb.ST^A99 (expired)	24-Jun-1996
+	Swedbank	SWEDa.ST	24-Jun-1996
+	Trelleborg	TRELb.ST	24-Jun-1996
+	Volvo	VOLVb.ST	24-Jun-1996

B. Complementary Regressions

Equal-weighted Eurostoxx50 index

Table 14 – Predictive regression on the equal-weighted excess returns and Eurostoxx50 excess returns for the complete time series

VARIABLES	(1) $Re_{ES50, EW, t}$	(2) $Re_{ES50, EW, t}$	(3) $Re_{ES50, EW, t}$	(4) $Re_{ES50, t}^{*}$	(5) $Re_{ES50, EW, t}$	(6) $Re_{ES50, EW, t}$	(7) $Re_{ES50, EW, t}$
$AC_{ES50, EW, t-1}$	-0.040		-0.042	-0.026			-0.056
	(-1.27)		(-1.33)	(-0.68)			(-1.05)
$AV_{ES50, EW, t-1}$		-0.266	-0.286	-0.237			1.203
		(-1.01)	(-1.09)	(-0.75)			(1.58)
$VAR\text{-}I_{ES50, EW, t-1}$					-3.069**		-5.158
					(-2.04)		(-1.09)
$VAR\text{-}M_{ES50, EW, t-1}$						-2.568*	
						(-1.73)	
$Re_{ES50, EW, t-1}$							0.222***
							(3.05)
$Rf_{ES50, t-1}$							-10.057***
							(-3.55)
Constant	0.008	0.005	0.011*	0.005	0.007*	0.006	0.024**
	(1.41)	(1.15)	(1.76)	(0.68)	(1.76)	(1.55)	(2.02)
Observations	233	233	233	233	233	233	232
R-squared	0.007	0.004	0.012	0.004	0.018	0.013	0.146

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Sub-periods of the value-weighted Eurostoxx50 index

Table 15 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns during the "Dotcom crisis" between

VARIABLES	(1) $Re_{ES50, VW, t}$	(2) $Re_{ES50, VW, t}$	(3) $Re_{ES50, VW, t}$	(4) $Re_{ES50, t}^{*}$	(5) $Re_{ES50, VW, t}$	(6) $Re_{ES50, VW, t}$	(7) $Re_{ES50, VW, t}$
$AC_{ES50, VW, t-1}$	0.299		0.227	0.315			0.555
	(1.07)		(0.76)	(0.91)			(1.01)
$AV_{ES50, VW, t-1}$		2.178	1.662	7.083**			3.699
		(1.08)	(0.77)	(2.82)			(0.70)
$VAR\text{-}I_{ES50, VW, t-1}$					5.556		-13.656
					(0.55)		(-0.31)
$VAR\text{-}M_{ES50, VW, t-1}$						13.808	
						(1.30)	
$Re_{ES50, VW, t-1}$							0.358
							(0.61)
$Rf_{ES50, t-1}$							-18.740
							(-0.60)
Constant	-0.044	-0.047	-0.061	-0.151***	-0.025	-0.035*	-0.032
	(-1.63)	(-1.59)	(-1.74)	(-3.71)	(-1.39)	(-2.07)	(-0.27)
Observations	16	16	16	16	16	16	16
R-squared	0.076	0.077	0.116	0.470	0.021	0.107	0.414

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Table 16 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns during the "Sovereign debt crisis" between

VARIABLES	(1) $\mathbf{Re}_{ES50, VW, t}$	(2) $\mathbf{Re}_{ES50, VW, t}$	(3) $\mathbf{Re}_{ES50, VW, t}$	(4) $\mathbf{Re}_{ES50, t}^{*}$	(5) $\mathbf{Re}_{ES50, VW, t}$	(6) $\mathbf{Re}_{ES50, VW, t}$	(7) $\mathbf{Re}_{ES50, VW, t}$
$\mathbf{AC}_{ES50, VW, t-1}$	-0.171		-0.193	-0.229			-0.464
	(-0.95)		(-1.09)	(-1.27)			(-1.16)
$\mathbf{AV}_{ES50, VW, t-1}$		3.040	3.266	2.703			-6.776
		(1.30)	(1.39)	(1.13)			(-0.45)
$\mathbf{VAR\text{-}I}_{ES50, VW, t-1}$					8.196		50.319
					(0.92)		(0.83)
$\mathbf{VAR\text{-}M}_{ES50, VW, t-1}$						6.498	
						(0.79)	
$\mathbf{Re}_{ES50, VW, t-1}$							0.307
							(1.32)
$\mathbf{Rf}_{ES50, t-1}$							-57.113*
							(-1.85)
Constant	0.043	-0.033	0.016	0.027	-0.023	-0.019	0.138
	(0.86)	(-1.21)	(0.30)	(0.52)	(-0.87)	(-0.76)	(1.31)
Observations	19	19	19	19	19	19	19
R-squared	0.050	0.090	0.153	0.143	0.047	0.036	0.461

t-statistics in parentheses for OLS standard errors.

***** p<0.01, ** p<0.05, * p<0.1**

Table 17 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns during the "Subprime mortgage crisis" between

VARIABLES	(1) $\mathbf{Re}_{ES50, VW, t}$	(2) $\mathbf{Re}_{ES50, VW, t}$	(3) $\mathbf{Re}_{ES50, VW, t}$	(4) $\mathbf{Re}_{ES50, t}^{*}$	(5) $\mathbf{Re}_{ES50, VW, t}$	(6) $\mathbf{Re}_{ES50, VW, t}$	(7) $\mathbf{Re}_{ES50, VW, t}$
$\mathbf{AC}_{ES50, VW, t-1}$	-0.005		0.002	-0.137			0.219
	(-0.02)		(0.01)	(-0.41)			(0.65)
$\mathbf{AV}_{ES50, VW, t-1}$		-0.141	-0.141	-0.194			0.979
		(-0.21)	(-0.20)	(-0.23)			(0.45)
$\mathbf{VAR\text{-}I}_{ES50, VW, t-1}$					-1.945		-6.005
					(-0.52)		(-0.47)
$\mathbf{VAR\text{-}M}_{ES50, VW, t-1}$						-1.255	
						(-0.31)	
$\mathbf{Re}_{ES50, VW, t-1}$							0.220
							(0.87)
$\mathbf{Rf}_{ES50, t-1}$							-24.841
							(-1.64)
Constant	-0.023	-0.021	-0.021	-0.006	-0.017	-0.020	0.037
	(-0.59)	(-1.11)	(-0.52)	(-0.13)	(-1.03)	(-1.16)	(0.51)
Observations	23	23	23	23	23	23	23
R-squared	0.000	0.002	0.002	0.013	0.013	0.005	0.318

t-statistics in parentheses for OLS standard errors.

***** p<0.01, ** p<0.05, * p<0.1**

Table 18 – Predictive regression on the value-weighted excess returns and Eurostoxx50 excess returns during market downturn periods, defined as the collapsed time series of the "Dotcom", "Sovereign Debt" and "Subprime Mortgage" crisis

VARIABLES	(1) $Re_{ES50, VW, t}$	(2) $Re_{ES50, VW, t}$	(3) $Re_{ES50, VW, t}$	(4) $Re_{ES50, t}^{*}$	(5) $Re_{ES50, VW, t}$	(6) $Re_{ES50, VW, t}$	(7) $Re_{ES50, VW, t}$
$AC_{ES50, VW, t-1}$	0.041		0.041	0.041			-0.153
	(0.52)		(0.50)	(0.43)			(-1.15)
$AV_{ES50, VW, t-1}$		-0.062	-0.034	0.041			-0.250
		(-0.11)	(-0.06)	(0.06)			(-0.16)
$VAR\text{-}I_{ES50, VW, t-1}$					-0.445		5.257
					(-0.15)		(0.58)
$VAR\text{-}M_{ES50, VW, t-1}$						0.810	
						(0.26)	
$Re_{ES50, VW, t-1}$							0.312**
							(2.26)
$Rf_{ES50, t-1}$							-19.335**
							(-2.65)
Constant	-0.021	-0.014	-0.021	-0.027	-0.014	-0.017	0.058
	(-1.43)	(-1.26)	(-1.16)	(-1.27)	(-1.34)	(-1.62)	(1.56)
Observations	58	58	58	58	58	58	58
R-squared	0.005	0.000	0.005	0.003	0.000	0.001	0.255

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Table 19 – Descriptive statistics for the value-weighted independent variables for the Eurostoxx50 index for the market downturn period

	Observations	Mean	Min	Max	STD
$AC_{ES50, VW, t-1}$	39	.1953256	.0563919	.3867823	.0822513
$AV_{ES50, VW, t-1}$	39	.0164354	.0031981	.0752632	.0157257
$VAR\text{-}M_{ES50, VW, t-1}$	39	.0028888	.0005443	.0121075	.0026122
$VAR\text{-}I_{ES50, VW, t-1}$	39	.0029431	.000499	.0145323	.0028193
$Re_{ES50, VW, t-1}$	39	-.0073702	-.1413318	.1089615	.0553712
$Rf_{ES50, t-1}$	39	.0020628	.0004513	.0044657	.0012916

Table 20 – Correlation matrix for the value-weighted independent variables and the primary dependent variable, value-weighted excess return in period t for the Eurostoxx50 index during market downturn periods

	$Re_{ES50, VW, t}$	$AC_{ES50, VW, t-1}$	$AV_{ES50, VW, t-1}$	VAR-M $_{ES50, VW, t-1}$	VAR-I $_{ES50, VW, t-1}$	$Re_{ES50, VW, t-1}$	$Rf_{ES50, t-1}$
$Re_{ES50, EW, t}$	1.0000						
$AC_{ES50, VW, t-1}$	0.2823	1.0000					
$AV_{ES50, VW, t-1}$	-0.1520	-0.2551	1.0000				
$VAR\text{-}M_{ES50, VW, t-1}$	-0.0512	0.1566	0.8775	1.0000			
$VAR\text{-}I_{ES50, VW, t-1}$	-0.1086	0.0744	0.8991	0.9852	1.0000		
$Re_{ES50, VW, t-1}$	0.3322	0.2508	-0.4103	-0.2979	-0.3802	1.0000	
$Rf_{ES50, t-1}$	-0.5101	-0.4672	0.5015	0.3537	0.3952	-0.4666	1.0000

Equal-weighted OMXS30 index

Table 21 – Predictive regression on the equal-weighted excess returns and OMXS30 excess returns for the entire time series

VARIABLES	(1) $Re_{OMX, EW, t}$	(2) $Re_{OMX, EW, t}$	(3) $Re_{OMX, EW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, EW, t}$	(6) $Re_{OMX, EW, t}$	(7) $Re_{OMX, EW, t}$
$AC_{OMX, EW, t-1}$	0.021		0.026	0.039			0.008
	(0.86)		(1.05)	(1.62)			(0.26)
$AV_{OMX, EW, t-1}$		-0.217	-0.288	-0.266			0.014
		(-0.74)	(-0.96)	(-0.92)			(0.02)
$VAR\text{-}I_{OMX, EW, t-1}$					-0.104		0.574
					(-0.17)		(0.43)
$VAR\text{-}M_{OMX, EW, t-1}$						-0.188	
						(-0.35)	
$Re_{OMX, EW, t-1}$							0.108
							(1.56)
$Rf_{OMX, t-1}$							-9.184**
							(-2.59)
Constant	-0.004	0.007	-0.002	-0.009	0.004	0.005	0.013
	(-0.39)	(1.27)	(-0.24)	(-0.97)	(0.95)	(1.05)	(0.90)
Observations	233	233	233	233	233	233	232
R-squared	0.003	0.002	0.007	0.013	0.000	0.001	0.054

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Sub-periods of the value-weighted OMXS30 index

Table 22 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns during market downturn periods during the "Dotcom" crisis

VARIABLES	(1) $Re_{OMX, VW, t}$	(2) $Re_{OMX, VW, t}$	(3) $Re_{OMX, VW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, VW, t}$	(6) $Re_{OMX, VW, t}$	(7) $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	0.608**		0.353	0.300			0.177
	(2.58)		(1.31)	(1.13)			(0.30)
$AV_{OMX, VW, t-1}$		5.494**	3.806	3.439			-4.461
		(2.86)	(1.68)	(1.54)			(-0.25)
$VAR\text{-}I_{OMX, VW, t-1}$					10.293***		16.689
					(3.22)		(0.47)
$VAR\text{-}M_{OMX, VW, t-1}$						11.444***	
						(3.33)	
$Re_{OMX, VW, t-1}$							0.046
							(0.17)
$Rf_{OMX, t-1}$							-60.555
							(-0.56)
Constant	-0.258**	-0.131***	-0.232**	-0.207**	-0.116***	-0.114***	0.050
	(-2.87)	(-3.34)	(-2.70)	(-2.46)	(-3.69)	(-3.79)	(0.16)
Observations	16	16	16	16	16	16	16
R-squared	0.322	0.369	0.443	0.390	0.425	0.442	0.494

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Table 23 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns during market downturn periods during the "Sovereign Debt" crisis

VARIABLES	(1) $Re_{OMX, VW, t}$	(2) $Re_{OMX, VW, t}$	(3) $Re_{OMX, VW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, VW, t}$	(6) $Re_{OMX, VW, t}$	(7) $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	0.059		0.198	0.186			-0.034
	(0.64)		(1.43)	(1.33)			(-0.20)
$AV_{OMX, VW, t-1}$		-0.808	-4.486	-2.850			-34.957**
		(-0.35)	(-1.32)	(-0.83)			(-2.29)
$VAR\text{-}I_{OMX, VW, t-1}$					0.057		38.334*
					(0.02)		(2.13)
$VAR\text{-}M_{OMX, VW, t-1}$						-0.221	
						(-0.08)	
$Re_{OMX, VW, t-1}$							0.289
							(1.26)
$Rf_{OMX, t-1}$							-15.173
							(-0.24)
Constant	-0.037	0.003	-0.079	-0.086	-0.004	-0.003	0.111
	(-0.69)	(0.13)	(-1.29)	(-1.39)	(-0.22)	(-0.14)	(0.83)
Observations	19	19	19	19	19	19	19
R-squared	0.024	0.007	0.120	0.104	0.000	0.000	0.429

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Table 24 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns during market downturn periods during the "Subprime Mortgage" crisis

VARIABLES	(1) $Re_{OMX, VW, t}$	(2) $Re_{OMX, VW, t}$	(3) $Re_{OMX, VW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, VW, t}$	(6) $Re_{OMX, VW, t}$	(7) $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	-0.070		-0.117	-0.175			0.453
	(-0.46)		(-0.70)	(-1.25)			(1.41)
$AV_{OMX, VW, t-1}$		0.699	1.166	2.364			20.886
		(0.46)	(0.70)	(1.69)			(1.56)
$VAR\text{-}I_{OMX, VW, t-1}$					0.249		-29.934
					(0.13)		(-1.55)
$VAR\text{-}M_{OMX, VW, t-1}$						0.221	
						(0.10)	
$Re_{OMX, VW, t-1}$							-0.169
							(-0.78)
$Rf_{OMX, t-1}$							-38.370*
							(-2.07)
Constant	0.013	-0.034	0.015	0.022	-0.024	-0.024	-0.186
	(0.17)	(-1.04)	(0.20)	(0.33)	(-0.84)	(-0.83)	(-0.96)
Observations	23	23	23	23	23	23	23
R-squared	0.010	0.010	0.034	0.140	0.001	0.000	0.384

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

Table 25 – Predictive regression on the value-weighted excess returns and OMXS30 excess returns during market downturn periods, defined as the collapsed time series of the "Dotcom", "Sovereign Debt" and "Subprime Mortgage" crisis

VARIABLES	(1) $Re_{OMX, VW, t}$	(2) $Re_{OMX, VW, t}$	(3) $Re_{OMX, VW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, VW, t}$	(6) $Re_{OMX, VW, t}$	(7) $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	0.094		0.082	0.080			0.257*
	(1.28)		(1.11)	(1.19)			(2.01)
$AV_{OMX, VW, t-1}$		1.046	0.867	1.322			12.667***
		(1.11)	(0.91)	(1.53)			(2.79)
$VAR\text{-}I_{OMX, VW, t-1}$					1.329		-16.781**
					(0.99)		(-2.38)
$VAR\text{-}M_{OMX, VW, t-1}$						1.592	
						(1.04)	
$Re_{OMX, VW, t-1}$							0.029
							(0.24)
$Rf_{OMX, t-1}$							-31.449***
							(-3.17)
Constant	-0.064*	-0.034*	-0.071*	-0.078**	-0.030*	-0.030*	-0.110
	(-1.74)	(-1.97)	(-1.89)	(-2.27)	(-1.95)	(-1.99)	(-1.50)
Observations	58	58	58	58	58	58	58
R-squared	0.029	0.022	0.043	0.076	0.017	0.019	0.282

t-statistics in parentheses for OLS standard errors.
***** p<0.01, ** p<0.05, * p<0.1**

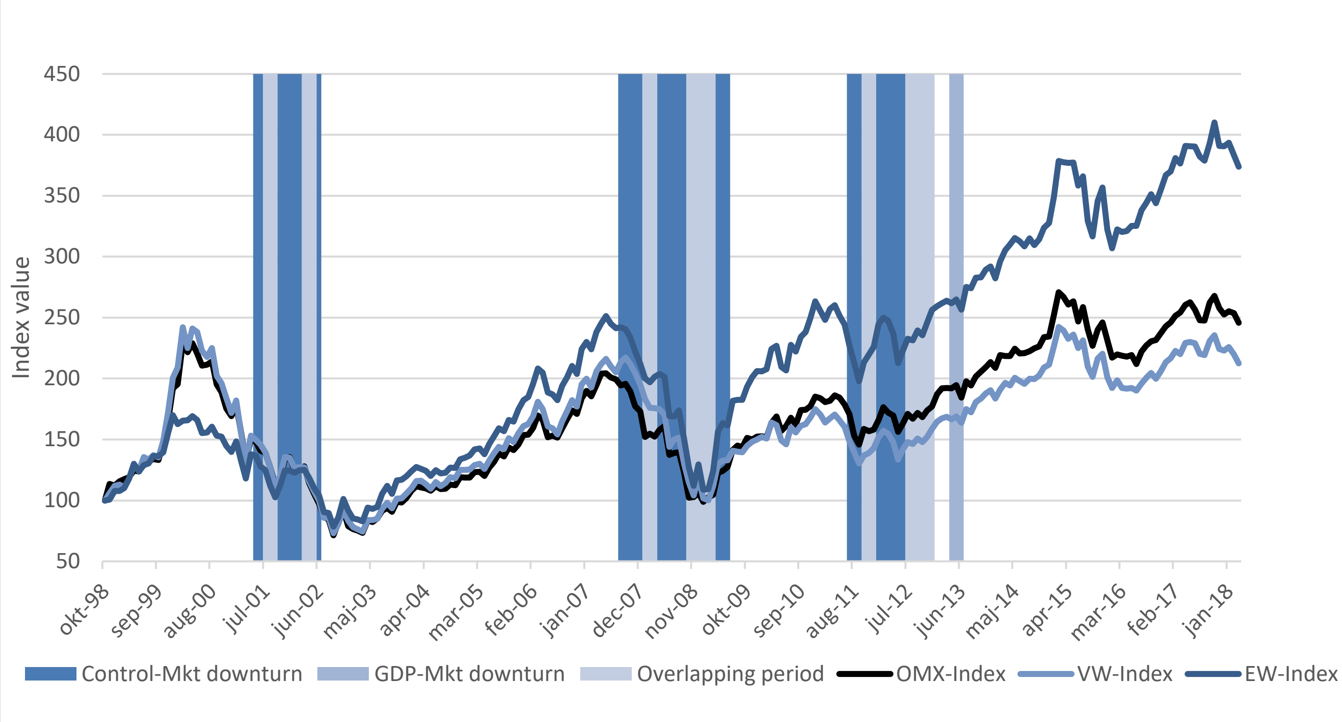
Table 26 – Descriptive statistics for the value-weighted independent variables for the OMXS30 index during the market downturn period defined by country GDP growth

	$Re_{ES50, VW, t}$	$AC_{ES50, VW, t-1}$	$AV_{ES50, VW, t-1}$	VAR-M $_{ES50, VW, t-1}$	VAR-I $_{ES50, VW, t-1}$	$Re_{ES50, VW, t-1}$	$Rf_{ES50, t-1}$
$Re_{ES50, EW, t}$	1.0000						
$AC_{ES50, VW, t-1}$	0.2421	1.0000					
$AV_{ES50, VW, t-1}$	-0.1697	0.3640	1.0000				
$VAR\text{-}M_{ES50, VW, t-1}$	-0.0879	0.5415	0.9717	1.0000			
$VAR\text{-}I_{ES50, VW, t-1}$	-0.0930	0.5385	0.9705	0.9984	1.0000		
$Re_{ES50, VW, t-1}$	0.1304	0.0030	-0.4931	-0.4134	-0.4123	1.0000	
$Rf_{ES50, t-1}$	-0.6252	-0.0968	0.5722	0.4510	0.4524	-0.4959	1.0000

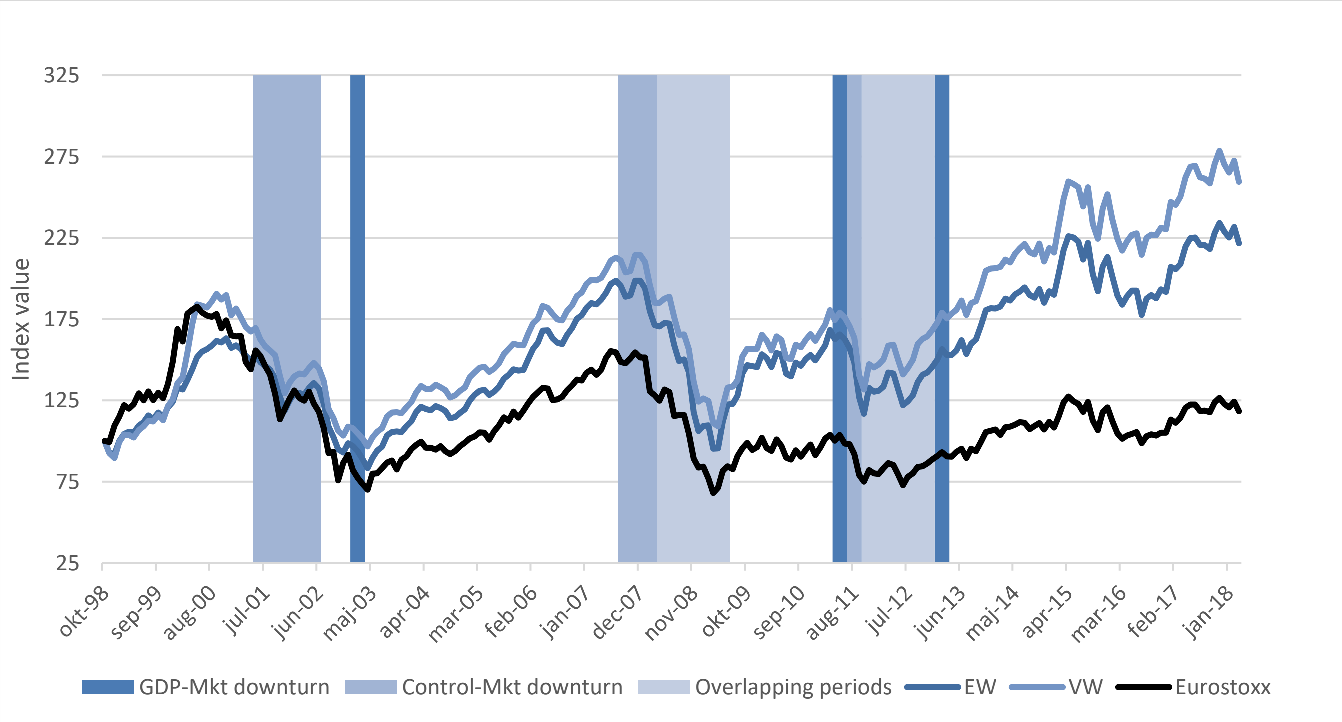
Table 27 – Correlation matrix for the value-weighted independent variables and the primary dependent variable, value-weighted excess return in period t for the OMXS30 index during market downturn periods defined by GDP growth

	Observations	Mean	Min	Max	STD
$AC_{OMX, VW, t-1}$	29	.5059612	.2209389	.7825333	.1489766
$AV_{OMX, VW, t-1}$	29	.0142683	.0026168	.05863	.0126353
$VAR\text{-}M_{OMX, VW, t-1}$	29	.0078808	.0007025	.0366307	.0083776
$VAR\text{-}I_{OMX, VW, t-1}$	29	.0089996	.0009035	.0406785	.0095773
$Re_{OMX, VW, t-1}$	29	-.0247658	-.1587582	.1295904	.0676961
$Rf_{OMX, t-1}$	29	.0021269	.000808	.0038246	.0011502

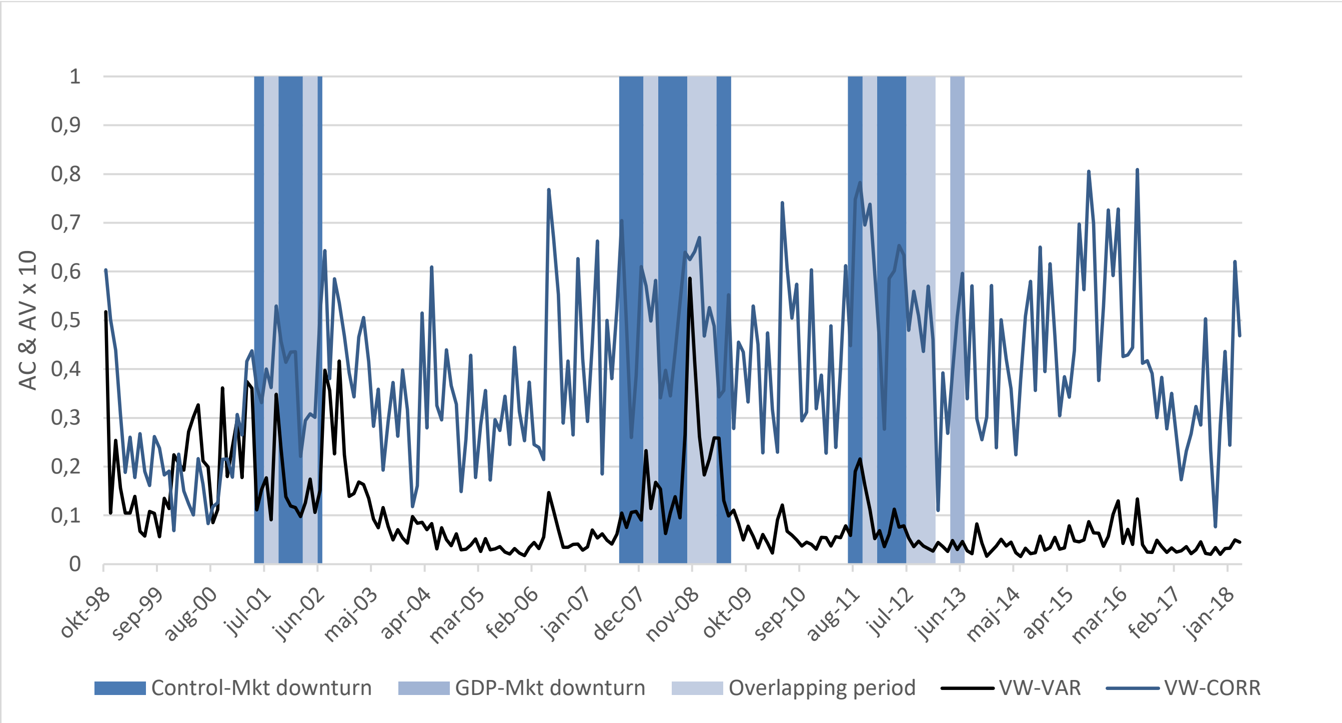
Graph 2 – Actual, value-weighted and equal-weighted return development over the entire time period for the OMXS30 index



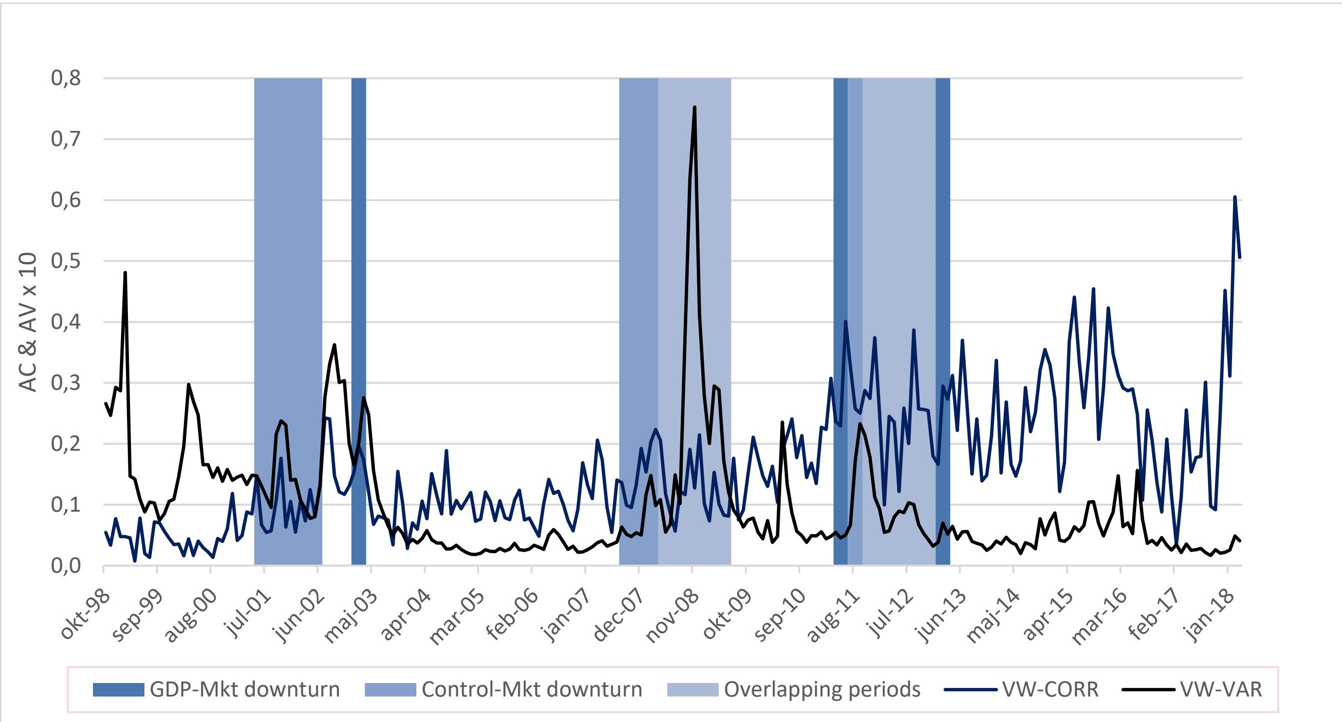
Graph 3 – Actual, value-weighted and equal-weighted return development over the entire time period for the Eurostoxx50 index



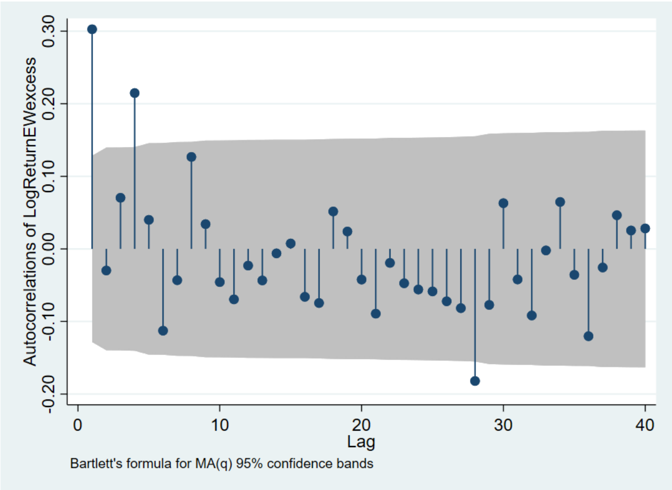
Graph 4 – Value-weighted constituent correlation and variance multiplied with 10 over the entire time period for the OMXS30 index



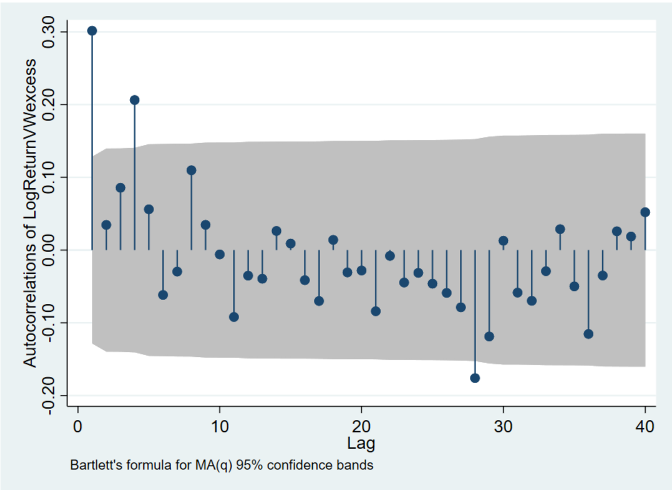
Graph 5 – Value-weighted constituent correlation and variance multiplied with 10 over the entire time period for the Eurostoxx50 index



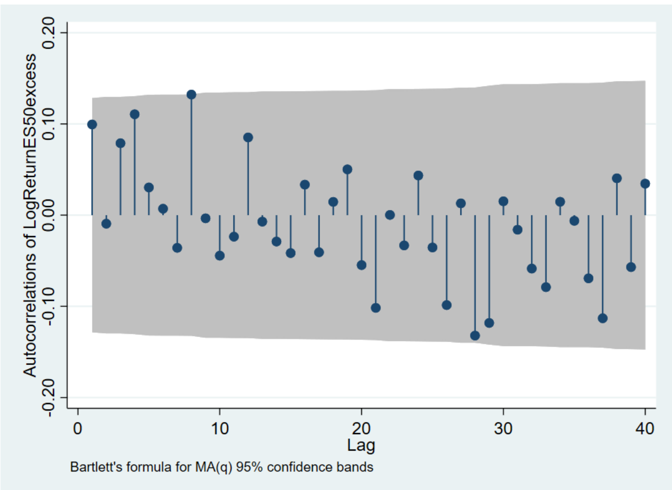
Graph 6 – Barlett correlogram for an equal-weighted excess return for the Eurostoxx50 index



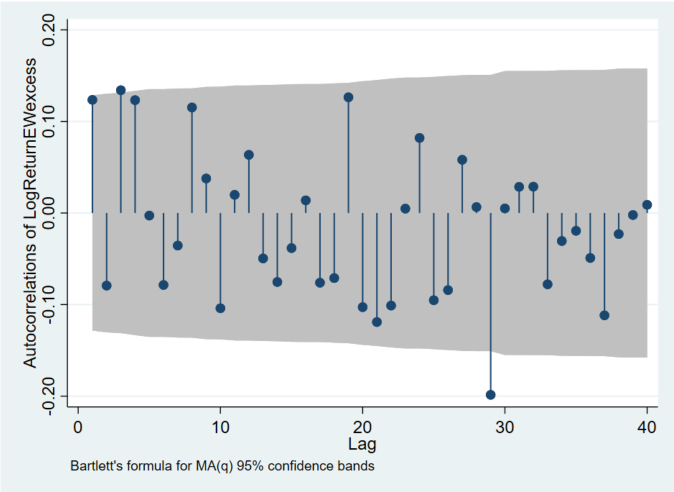
Graph 7 – Barlett correlogram for a value-weighted excess return for the Eurostoxx50 index



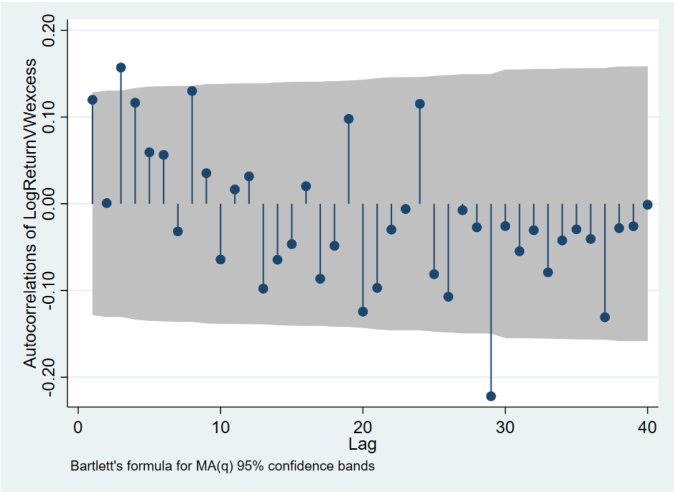
Graph 8 – Barlett correlogram for the actual excess return for the Eurostoxx50 index



Graph 9 – Barlett correlogram for the equal-weighted excess return for the Eurostoxx50 index



Graph 10 – Barlett correlogram for the value-weighted excess return for the Eurostoxx50 index



Graph 11 – Barlett correlogram for the actual excess return for the Eurostoxx50 index

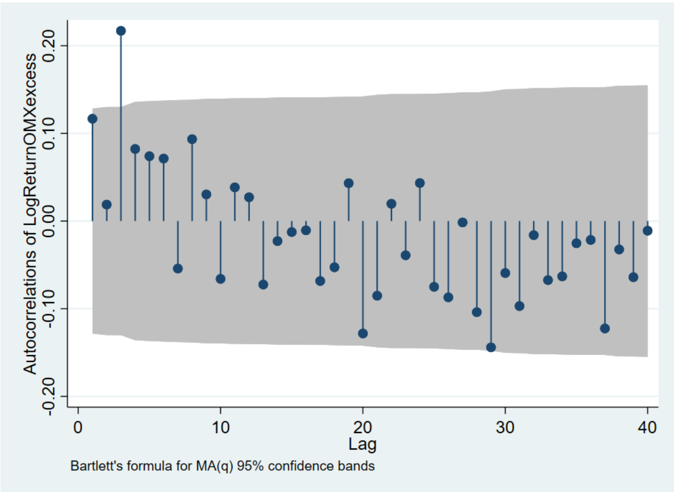


Table 28 – Predictive regression on the value-weighted excess return for Eurostoxx50 with a newey-west t-statistics

VARIABLES	(1) $Re_{ES50, VW, t}$	(2) $Re_{ES50, VW, t}$	(3) $Re_{ES50, VW, t}$	(4) $Re_{ES50, t}^{*}$	(5) $Re_{ES50, VW, t}$	(6) $Re_{ES50, VW, t}$	(7) $Re_{ES50, VW, t}$
$AC_{ES50, VW, t-1}$	-0.0335		-0.0393	-0.0254			-0.0776
	(-1.09)		(-1.30)	(-0.76)			(-1.70)
$AV_{ES50, VW, t-1}$		-0.345	-0.402	-0.341			0.395
		(-0.89)	(-1.11)	(-0.81)			(0.60)
$VAR\text{-}I_{ES50, VW, t-1}$					-3.390		-0.241
					(-1.91)		(-0.05)
$VAR\text{-}M_{ES50, VW, t-1}$						-3.230	
						(-1.60)	
$Re_{ES50, VW, t-1}$							0.233^{***}
							(3.56)
$Rf_{ES50, t-1}$							-9.360^{***}
							(-3.61)
Constant	0.00786	0.00597	0.0128^{*}	0.00627	0.00785^{*}	0.00718	0.0279^{**}
	(1.20)	(1.59)	(2.09)	(0.85)	(2.19)	(1.90)	(2.93)

***t* statistics in parentheses for Newey-west t-statistics**
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 29 – Predictive regression on the value-weighted excess return for OMXS30 with a newey-west t-statistics

VARIABLES	(1) $Re_{OMX, VW, t}$	(2) $Re_{OMX, VW, t}$	(3) $Re_{OMX, VW, t}$	(4) $Re_{OMX, t}^{*}$	(5) $Re_{OMX, VW, t}$	(6) $Re_{OMX, VW, t}$	(7) $Re_{OMX, VW, t}$
$AC_{OMX, VW, t-1}$	0.0117		0.0145	0.0217			0.00390
	(0.43)		(0.54)	(0.85)			(0.09)
$AV_{OMX, VW, t-1}$		-0.354	-0.386	-0.198			0.238
		(-0.76)	(-0.82)	(-0.41)			(0.09)
$VAR\text{-}I_{OMX, VW, t-1}$					-0.337		0.323
					(-0.44)		(0.07)
$VAR\text{-}M_{OMX, VW, t-1}$						-0.295	
						(-0.34)	
$Re_{OMX, VW, t-1}$							0.105
							(1.38)
$Rf_{OMX, t-1}$							-9.395
							(-1.84)
Constant	-0.00311	0.00509	-0.000404	-0.00451	0.00325	0.00280	0.0113
	(-0.25)	(1.06)	(-0.03)	(-0.41)	(0.64)	(0.55)	(0.63)

***t* statistics in parentheses for Newey-west t-statistics**
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$