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Asymmetric Covariance, Volatility and Time-Varying Risk Premium: Evidence from the Finnish Stock Market

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1st Examiner: Post-doctoral Researcher Jan Stoklasa
2nd Examiner: Professor Mikael Collan

Abstract

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It appears that stock return and its volatility are negatively correlated. Negative returns cause volatility to increase more than positive returns of the same magnitude. This empirical regularity is often termed as asymmetric volatility in the burgeoning literature. Two competing theoretical explanations for observed volatility asymmetry at the firm level have been put forward by researchers: leverage effect, and volatility feedback effect (i.e., time-varying risk premia). Using a more up-to-date data in the context of the Finnish stock market, the thesis aims to investigate observed volatility asymmetry within the framework of volatility feedback effect. In other words, the study examines asymmetric behavior of conditional variances and covariance, and their impact on risk premium under the time-varying risk premium hypothesis. The research contributes to the extant literature on the volatility asymmetry under the volatility feedback effect in the context of the Finnish stock market since most previous studies were based on other developed stock markets. Apart from studies under volatility feedback effect in the Finnish stock market, it is the only study concentrating directly on volatility feedback effect to explain observed volatility asymmetry. Hence, the study provides valuable insights into the return-volatility dynamics and their asymmetric functioning to practitioners as well as investors.

The analysis is approached employing econometric models such as univariate EGARCH, ADCC-EGARCH in modeling conditional covariance. The results suggest that market conditional volatility increases expected stock risk premium through a change in covariance, and so does more when market return is asymmetric. The findings reveal that evidence for volatility feedback effect to explain observed volatility asymmetry is weak. Rather, evidence for significant firm-specific conditional volatility is found. The study puts forward reasons for firm-specific conditional volatility is due to firm-level leverage, and/or market inefficiency. The results provide practical implications and insights for potential investors and portfolio managers regarding the benefits of investing and diversifying portfolio in the Finnish stock market.

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1. Introduction

Volatility, as a measure of risk, is an important concept in the financial market. Empirical literature establishes the fact that volatility in the financial market varies over time [Bollerslev (1986), Orskaug (2009), Skregelid (2009)]. This phenomenon was more transparent after October 1987 stock market crash and the recent financial crisis. Understanding the way of how market volatility changes improves our decision making in many areas of finance, e.g., portfolio diversification, asset allocation, options pricing, and risk management. Since the market volatility is non-constant, traditional constant measure of risk (i.e., standard deviation) is unable to explain the volatility dynamics. One way to model this non-constant variance, often referred to as heteroskedasticity, is to employ Engle's ARCH process. Engle (1982) introduced the concept of conditional heteroskedasticity. Since then, researchers have long been documenting heteroskedasticity in the stock market returns using ARCH effects. The proliferation of many econometric models, such as generalized ARCH-M, exponential GARCH, GJR, enable researchers to capture the effects of conditional second moments.

Several researches have been documented that stock returns and stock return volatility are negatively correlated [Bae et al. (2006), Bollerslev et al. (2006)]. A negative correlation persists when negative stock returns (i.e., decrease in stock returns) lead to higher subsequent period volatility (i.e., increase in stock volatility). In other words, negative (positive) returns cause conditional volatility to rise (fall) in response to bad (good) news. This empirical phenomenon, often regarded as asymmetric volatility in the literature, has been studied both for individual stocks and for market indices [Braun et al. (1995), Cho and Engle (1999), Wu (2001)]. In fact, volatility asymmetry relies on the well-documented fact that a negative return shock of a firm causes volatility to increase more than a positive return shock of the same magnitude. In the finance literature, it is found that both leverage and volatility feedback effect are deemed as the explanation for this asymmetry. Both leverage effect and volatility feedback effect are defined in the following paragraphs (even more descriptively in the theoretical framework chapter). Each of these effects has its own interpretation, even though they together are part and parcel of a single process [Bekaert & Wu (2000)].

Black (1976) was the first to coin the term “leverage” or asymmetric effects and then Christie (1982) documents and explains the asymmetric volatility property of individual stock returns in the US. The explanation they suggest is the leverage hypothesis which relies on the fact that when stock prices fall, it causes firms’ leverage ratio to increase because the relative weight of debt-to-equity rises. The increased leverage makes firms’ stock riskier, and thus, leading to a proportional increase in equity volatility. Since investors confront negative returns following stock prices fall, leverage effect indicates that a negative correlation exists between stock return and stock volatility.

The other plausible explanation for volatility asymmetry is the time-varying risk premium, also known as volatility feedback effect [Pindyck (1984), French et al. (1987), Campbell & Hentschel (1992)]. Volatility feedback theory relies on the fact that if volatility, as a measure of risk, is priced, then an expected increase in volatility raises the required return on equity, leading to an immediate stock price decline. It can be noted that volatility feedback is primarily based on a positive trade-off between risk and return. However, since the increased volatility causes negative returns to appear, a negative correlation persists between stock volatility and next-period stock return. Campbell and Hentschel (1992) study the volatility feedback effect using quadratic GARCH and suggest that it has impact on returns. Both the leverage effect and volatility effect alone cannot account for the fully-fledged volatility responses [Bekaert and Wu (2000), Dean and Faff (2004), Wu (2001)].

Researchers often confront the issue whether to find asymmetry in covariance or beta. Note that finding beta asymmetry at the firm level generally implies estimating stock beta or commonly used CAPM beta. However, some researchers emphasize on beta asymmetry by modeling the conditional beta to explain the volatility asymmetry at the firm level. Braun, Nelson, and Sunier (1995) find weaker evidence of time-varying betas. Bekaert and Wu (2000) argue that asymmetry is more likely to be found in conditional covariances but have not found any support for conditional beta from the sample. Dean and Faff (2004) further argue that any asymmetry in beta is difficult to detect since shocks affect both the conditional variance and conditional covariance in a similar way. Even though beta remains constant in many economic models (CAPM), a rise in the market’s conditional variance requires a proportional rise in the conditional covariance, and if the market’s variance is asymmetric, the firm’s covariance will exhibit asymmetry. Hence, a market’s

shock that raises the market conditional volatility increases the required risk premium on the firm and causes the volatility feedback effect. To find the asymmetry in beta, researchers confront an artificial construct that may have asymmetry in both numerator and denominator. That is, the conditional beta is a function of the conditional covariance and conditional market volatility, particularly when both series exhibit asymmetry, it is difficult to detect beta asymmetry. Furthermore, researchers assert that there is no model to detect beta asymmetry at the firm level. In contrast, Cho and Engle (1999) document an asymmetric effect of news on the beta of individual stocks when using daily return series data and provide support for time-varying risk premiums. They contend that stock price aggregation and use of monthly data by Braun et al. (1995) significantly reduce the chances of detecting asymmetry effects in beta. Furthermore, Koutmos and Kniff (2002) study time-varying betas and asymmetry in the Finnish stock market by constructing size based equally weighted portfolios and find evidence of time variation in betas and beta asymmetry which explain the short-term dynamics of systematic risk. However, they do not find any covariance asymmetry. Therefore, researchers advocate that the use of conditional beta in estimating time-varying risk premiums can be inconclusive, rather time-varying covariance are more natural way to examine both volatility asymmetry and time-varying risk premiums.

Although studies document volatility transmission and asymmetry among the Nordic stock markets (Booth et al. 1997), conditional volatility and covariance asymmetry at the firm level has not been investigated thoroughly by many. This study attempts to fill a research gap in the domain of volatility asymmetry using a more up-to-date Finnish stock market data. Specifically, the thesis examines the volatility feedback hypothesis-one of the two explanations for volatility asymmetry- in the context of Finnish stock market. The rationale is that volatility feedback effect has not yet been studied at the firm level in the Finnish stock market. However, in their study, Kanniainen and Piche (2012) examine the joint dynamics of stock price, dividend, and volatility under the volatility feedback effect for option valuations. Since their study contributes to how options should be priced by considering time-varying price-dividend ratio (or dividend yield), this thesis concentrates on how stocks should be valued by determining the time-varying asymmetric relationship between return and its volatility under time-varying risk premium hypothesis. In addition, the work of Koutmos and Kniff (2002) do not put forward any explanations for volatility

asymmetry even though they find significant beta asymmetry by constructing portfolios. They do not find any significant results for covariance asymmetry, which might be one of the reasons for employing constant correlation model for conditional covariance is unrealistic when correlation between assets are time varying. However, researchers firmly emphasize that covariance asymmetry is more natural to happen. Therefore, volatility asymmetry at the firm level within the framework of volatility feedback effect is a worth investigation since it has potential implication on investors' risk-return trade-off. Risk premium tends to change over time because stock market volatility varies over time. Further, asymmetry effect into the risk-return relationship is an important consideration for investors when the market is turmoil. Investors' investing in stocks should consider such market behavior in estimating stock risk premium. Hirvonen (2016) explores the pricing and effect of liquidity risk on stock returns in the Finnish stock market and finds that investors are willing to pay a premium for having liquid assets during the period of declined market liquidity or returns. Hence, the findings of this study implicitly support the fact that investors in the Finnish stock market require higher expected return, i.e., liquidity premium is a part of total expected return, when market volatility increases due to declined market liquidity.

The study contributes to the empirical literature in the field of volatility asymmetry. Since the study analyzes observed volatility asymmetry at the firm level within the framework of time-varying risk premium hypothesis, the results suggest that market volatility increases firm-level volatility through changing covariance and therefore, effectively increasing risk premium. The study finds that the impact is greater when market volatility displays asymmetry and hence, exhibiting covariance asymmetry and higher risk premium. In addition, it is found that firm-specific conditional variances exhibit asymmetry effects in their parameter estimates and thus, affecting the average risk premium. Although time-varying risk premium hypothesis embracing CAPM does not explain firm-level asymmetry, the study states the causes of such asymmetry is due to firm-level leverage and/or market inefficiency. Furthermore, the results show that few stocks represent joint asymmetry effects in their parameter estimates. Evidence that volatility feedback effect is strong when the conditional covariance between market and stock returns is asymmetric is, therefore, found weak. Rather, firm-specific asymmetry effects are significant. The

findings of this study benefit investors, managers, and researchers to understand the asymmetric behavior of return-volatility relationship in the Finnish stock market.

1.1 Objectives

Using daily returns data of the OMX Helsinki 25 and its constituents, this thesis investigates asymmetric conditional volatility and asymmetric conditional covariance at the firm and market level and their implications on the time-varying risk premium. The aim is to examine the time-varying risk premium hypothesis only in the context of Finnish stock market. In other words, the thesis attempts to explain how much volatility asymmetry can be explained by the volatility feedback effect. Moreover, finding the effect of volatility feedback requires careful attention because several researchers claim that feedback effect is hardly to find in the lower-frequency data. More recently, it has been reported that it is difficult to find leverage, and volatility feedback effects in lower-frequency data, for example, in monthly data frequency these effects are reflected immediately and consequently, they are difficult to distinguish (Bollerslev et al. 2006). In fact, this is true that using monthly data Braun et al. (1995) end up with finding no asymmetry in beta. However, Cho and Engle (1999) find asymmetry effects using individual stocks daily return frequency and argue that when asymmetry effects are more likely to find in the daily data, Braun et al. (1995) did not find because of using monthly data and stock price aggregation reduced their chances of detecting asymmetry effects. Therefore, this thesis uses daily returns supporting the use of higher frequency data, however, recent researches find these effects prevailing in the intra-day returns. Despite the fact that more higher frequency data enable researchers to find these effects, daily data in this case is justified for two reasons: first, it meets the criteria of using higher frequency data, and second, some researchers were able to find these effects using daily data frequency. Moreover, finding these effects are not only limited to data frequency but to the methodology employed. Since Koutmos and Kniff (2002) construct size-based portfolios at the firm level, we consider individual stocks to be examined (Dean and Faff 2004). Finally, asymmetries and time-varying relations are reflected in the changing risk premium.

1.2 Research Questions & Analytical Models

The study attempts to answer the following questions:

1. Does conditional covariance respond positively to increases in market volatility at the firm level? In other words, do market shocks increase conditional market volatility and thus, conditional covariance?
2. Does negative shock at the market level increase the market risk premium and therefore, expected stock risk premium?
3. Does negative shock at both levels simultaneously increase covariance risk so that the combined effect is considerable?
4. Do negative market shock and positive firm shock simultaneously increase the required risk premium more than positive market shock and negative firm shock?
5. Is volatility feedback effect strong when the conditional covariance between market and stock returns is asymmetric?

Further explanations at this point are necessary to clarify how these listed questions will be answered. This thesis employs univariate Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) for market conditional volatility, and Asymmetric Dynamic Conditional Correlation (ADCC)-EGARCH for conditional covariance between market and stock returns. The first research question is examined by looking at the sign, and size parameters of the univariate EGARCH, and ADCC-EGARCH specification as well. The second, third, and fourth questions are answered by examining the impact of relevant shocks on the risk premium. The fifth question related to volatility feedback which reflects strong effect when it responds more to negative than to positive market return shocks. Also, the effect is evident when the asymmetry term of the joint estimates (market and stocks) is statistically significant in majority of the stocks and that is implied in estimating the average risk premium (see details in Discussion chapter).

1.3 Motivation & Contribution to Extant Literature

The motivation for this study is originated from the asymmetric behavior of stock markets. Researchers document that stock return and its volatility are negatively correlated [Cheung & Ng (1992), Bae et al. (2006)]. Because when negative (positive) returns appear in the market, this causes agents to revise upward (downward) estimates of the conditional volatility. This empirical regularity is often referred to as asymmetric volatility in the literature [Wu (2001), Engle & Ng (1993)]. The asymmetric nature of stock market volatility becomes apparent during a stock market crash when a large decline in stock prices is followed by a significant increase in market volatility, for example, October 1987 stock market crash [Siourounis (2002), Nelson (1991)]. Apart from this, two plausible reasons for such volatility asymmetry for individual stock returns have been put forward by financial researchers. Black (1976) first recognizes this fact and terms it 'Leverage effect' because, in his opinion, when stock prices decline, this causes firms' debt-to-equity ratio to increase and thus, leading to an increase in next-period return volatility. The other reason put forward by Pindyck (1984), French et al. (1987), Campbell & Hentschel (1992) is the 'volatility feedback effect' which explains that if volatility is priced, an anticipated increase in volatility raises the required return on equity, and thus, leading to an immediate stock price fall. Again, this stock price fall is reflected as negative return and hence, conditional volatility is negatively correlated with next-period return. In effect, the negative return reactivates the leverage effect and this process can last indefinitely (Wu 2001).

Though several studies assess the asymmetric property of volatility across different stock markets, and between stock and bond markets, investigation for volatility asymmetry at the firm level has been studied for some developed stock markets (mainly for US & Japanese equity markets). Observed volatility asymmetry upon embracing relevant theoretical framework at the firm level has not been investigated thoroughly in the Finnish stock market. However, in their study, Kanniainen and Piche (2012) examine the joint dynamics of stock price, dividend, and volatility under the volatility feedback effect for option valuations and find that the market price of diffusion return risk (or equity risk premium) affects option prices. Since their study contributes to how options should be priced by considering time-varying price-dividend ratio (or dividend yield), this thesis concentrates

on how stocks should be valued by determining the time-varying asymmetric relationship between return and its volatility under time-varying risk premium hypothesis. Hence, the focus of the thesis is not perfectly aligned with their study. This provides room for examining volatility asymmetry at the firm level, which, of course, have important implications for investors' risk-return trade-off. Treating heteroscedasticity with ARCH-type models, this thesis employs ADCC-EGARCH process for modeling volatility feedback. The findings of this study help us know to what extent observed volatility asymmetry in the Finnish stock market can be explained by the time-varying risk premium (or volatility feedback) hypothesis. A recent and up-to-date data is used for this analysis. The study assists practitioners and investors to understand the market's risk-return dynamics, manage their portfolios for risk management (diversification), asset allocation, and rebalancing.

1.4 Scope and Limitations of the Study

Examining volatility asymmetry within the framework of time-varying risk premium (volatility feedback) hypothesis has various pragmatic financial implications. Since volatility is non-constant and contains asymmetry effects, practitioners and investors are more likely to revise their estimates accurately. This helps them understand the stock market dynamism, and risk-return trade-off. Moreover, understanding how the volatility behaves asymmetrically improves our understandings about better risk management through portfolio diversification. Consequently, portfolio managers are more likely to be accurate in asset allocation and portfolio rebalancing.

The thesis studies only the volatility feedback effect- one of the two competing interpretations of volatility asymmetry at the firm level- and hence, it only investigates to what extent observed volatility asymmetry can be explained by the volatility feedback effect. However, another important interpretation for the volatility asymmetry at the market and firm level is the leverage effect hypothesis. This thesis provides a theoretical overview on which leverage effect is rooted in, however, does not explicitly test it from an empirical standpoint. Therefore, to what magnitude observed volatility asymmetry could be explained by the leverage hypothesis is not investigated in the thesis. Any further study

embracing the leverage effect hypothesis can establish a link between firm-specific shocks and risk premiums, through conditional covariance, the effect of volatility asymmetry would be stronger at the firm level, more so if the conditional covariance is asymmetric, as like the study done by Bekaert and Wu (2000). In addition, Finnish stock market is small, and less liquid compared to other equity markets. Furthermore, recent studies document that Finnish and Swedish stock market are not weak form-efficient. Thus, another limitation is that the results of this study cannot broadly be generalized to all stock markets, however, it might be comparable with stock markets which represent such characteristics as small size, less liquid, and absence of weak form-efficiency, which mostly exist in emerging equity markets.

1.5 Structure of the Study

This thesis has structured and organized in eight chapters. The first chapter includes an introduction of the study, objectives as well as research questions, motivation and contribution to extant literature, and scope and limitations of the study. Chapter two introduces the theoretical framework under which the study is framed-up. The third chapter provides an overview of the literature review that includes relevant previous studies conducted in the field of volatility asymmetry. This chapter expatiates more on various findings from previous studies about asymmetric volatility at the market and firm level, volatility transmission and spillover across stock markets.

Chapter four provides a general overview of methodology and various models (or family of models) used in the study. At the end of the chapter four, the study discusses empirical framework employed for analysis purpose. Chapter five presents financial time series data for the study. It specifies characteristics of the data with regards to descriptive statistics and tests for ARCH-type models to ensure that data is compatible for the methodology chosen. The sixth chapter discusses the empirical results and findings from the estimation and attempts to answer research questions. At last, chapter seven provides a comprehensive conclusion of the study based on the findings as well as suggests practical implications for investors and financial managers. The study also identifies possible directions for further research.

2. Theoretical Framework

A review of the extant literature reveals two plausible explanations for volatility asymmetry: leverage effect hypothesis and time-varying risk premium hypothesis [Bekaert & Wu (2000), Wu (2001), Dean & Faff (2004), Bollerslev & Zhou (2006), Bollerslev et al. (2006)]. It has been firmly established that negative return shocks cause volatility to increase more than positive return shocks of the same magnitude [Nelson (1991), Bae et al. (2006), Olbrys & Majewska (2017)]. If this is the case, Black (1976) was the pioneer to coin the term "leverage" in which he states that stock prices fall cause firms' leverage ratio to increase, making the stock riskier and therefore, the higher changes in volatility. The leverage hypothesis implies that changes in volatility are observable in one-period-ahead if stock prices fall in the current period (Duffee 1995). Black's leverage hypothesis was empirically tested by Christie (1982) who finds and explains the asymmetric volatility property of individual stock returns in the US.

Several studies reveal the fact that leverage effects have been introduced to be synonymous with asymmetric volatility. Following Black and Christie, Duffee (1995) asserts that a negative correlation between returns and changes in volatility implied by the leverage effect occurs through a negative correlation between returns and one-period-ahead volatility, not through a positive correlation between returns and contemporaneous volatility. Using US stock market data, he shows that the reason for firms' stock return volatility rises after stock prices fall is a positive contemporaneous relation between firms' stock return and stock return volatility. Because he finds that firms with higher debt-to-equity ratio also exhibit a stronger negative correlation between returns and contemporaneous volatility although the leverage effect implies that firms with higher debt-to-equity ratio should exhibit a stronger negative correlation between returns and next-period volatility. His study also finds that the positive contemporaneous relation is greatly pronounced for smaller firms (firms with lower market capitalization) and firms with little leverage (lower debt-to-equity ratio). However, Figlewski and Wang (2000) assess the leverage effect with a closer look and document that leverage is not a complete explanation of volatility asymmetry associated with positive and negative stock returns. In other words, the magnitude of the effect of current stock prices decline on subsequent volatility is too large to be attributable solely by the changes in financial leverage.

Furthermore, it is found that the asymmetric nature of return-volatility relationship is generally larger to market index returns than that for individual stocks [Andersen et. al (2001), Kim & Kon (1994)].

The other rational explanation for the volatility asymmetry is the time-varying risk premium, also known as volatility feedback effect. It argues that the asymmetric nature of volatility response to return shocks could simply reflect the existence of time-varying risk premium [Pindyck (1984), French et al. (1987), Campbell & Hentschel (1992)]. If volatility, as a measure of risk, is priced, a forecasted increase in volatility raises the required return on equity, leading to an immediate stock price decline. Hence, the stock price decline again causes negative return shocks and that the leverage effect is reactivated. It can be noteworthy that the fundamental difference between leverage effect and volatility feedback lies in the causality: leverage effects explain how negative return shocks produce higher next-period volatility, while the volatility feedback effects justify how an anticipated increase in volatility causes negative return shocks through a proportional increase in required return on equity [Bollerslev & Zhou (2006), Bollerslev et al. (2006)]. Therefore, in this sense, volatility feedback effect reinforces the leverage effect [Bekaert and Wu (2000), Dean and Faff (2004)]. To explain this phenomenon, three main assumptions underlie the volatility feedback theory. It assumes that volatility is persistent, a well-documented phenomenon reported by extensive researches. It further assumes that the conditional CAPM applies and that there exists a positive intertemporal relation between expected return and conditional variance. The increased volatility raises expected return and lowers stock prices, increasing volatility in case of bad news and dampening volatility in case of good news [Bekaert and Wu (2000), Wu (2001)].

2.1 Volatility feedback effect

To illustrate the role of covariance in volatility feedback and hence, asymmetric volatility, we assume that a conditional version of CAPM holds, that is, the market portfolio's expected excess return is the (constant) price of risk times the conditional variance of the market (Merton 1980)

$$E[r_{m,t}|\Psi_{t-1}] = \lambda_t \, \sigma^2_{m,t}|\Psi_{t-1} \qquad (1)$$

and the expected excess return on any stock or firm is the price of risk times the conditional covariance between the stock's return and the market.

$$E[r_{i,t}|\Psi_{t-1}] = \lambda_t \, cov(r_{i,t}\,, r_{m,t}|\Psi_{t-1}) \; \forall \, i \qquad (2)$$

and

$$\lambda_t = \frac{E[r_{m,t}|\Psi_{t-1}]}{E[(\sigma^2_{m,t})|\Psi_{t-1}]} \qquad (3)$$

Where $r_{i,t}$ and $r_{m,t}$ are the expected excess returns on an asset *i* and the market portfolio at time *t*. λ_t is the market price of risk at time *t*, Ψ_{t-1} denotes the information set at time *t-1*, and $\sigma^2_{m,t}$ is the estimated market conditional variance.

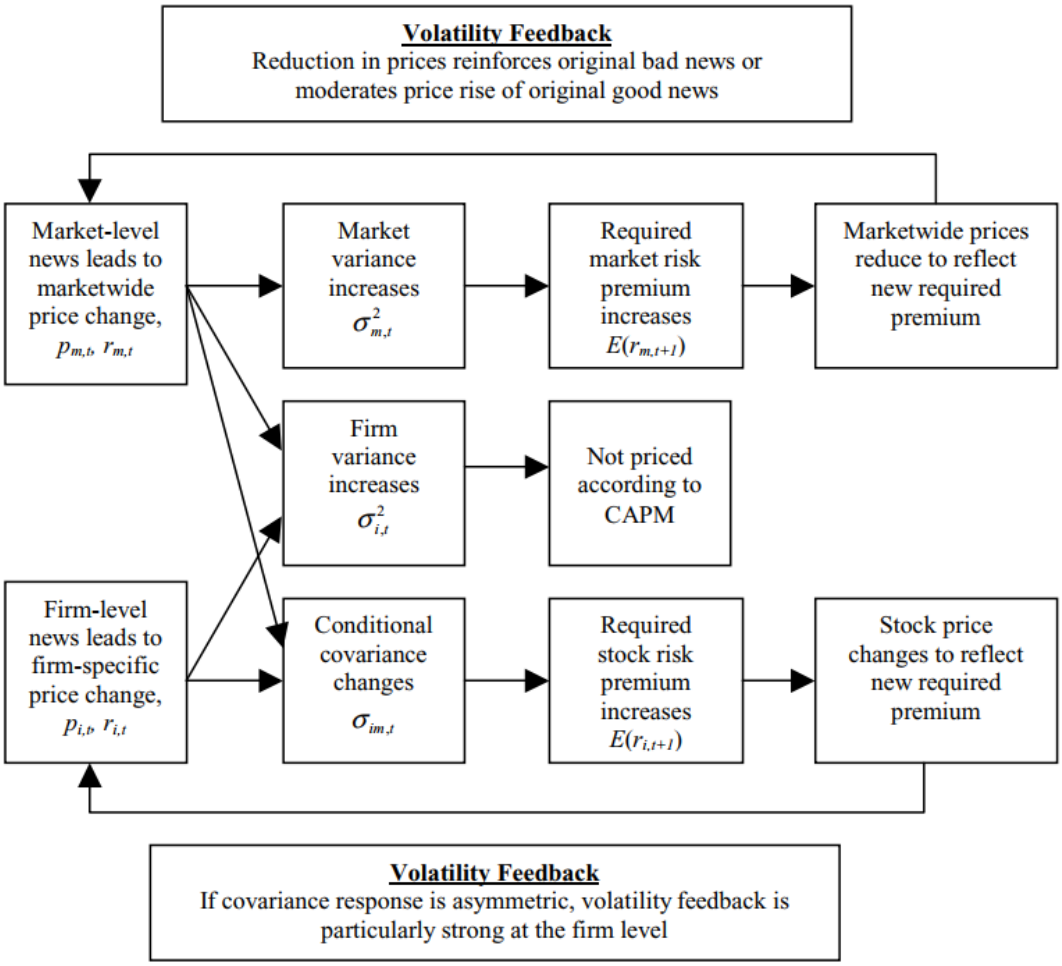

Figure 1: Flow of news effect at market and firm levels

[Dean & Faff (2004), Bekaert & Wu (2000)]

In figure 1, consider the effect of a general market-level news (shocks), say, the release of bad news at the market level has two effects. First, news is evidence of higher current volatility in the market, which will, ceteris paribus, increase the covariance between asset returns and market returns. Because volatility and conditional covariance are persistent, investors will revise upward estimates of future conditional covariance, which will require a higher expected return (according to the CAPM), leading to an immediate decline in the current value of the market. The price decline will continue until the expected return is high enough in equilibrium. Hence, a negative return shock may generate an anticipated increase in conditional volatility, which again leads to an immediate price drop, as predicted by the volatility feedback hypothesis. Thus, the volatility feedback effect reinforces initial price drop and creates further volatility in the market. Second, the market-wide price drop leads to higher leverage at the market level, and this will increase the required risk premium across the market and create higher covariance, again reinforcing the price drop and create further volatility in the market. That is, leverage effect reinforces the volatility feedback effect and that these effects happen simultaneously and often interact each other.

When good news arrives in the market, there are again two effects. First, news brings about higher current period market volatility and investors will again revise upward their estimates of next period's covariance. When volatility increases, prices decline to induce higher expected returns, dampening the initial price movement. Second, the market rally (positive return shock) reduces leverage, decreases conditional volatility at the market level, and thus, the required market risk premium. Overall, the net impact on stock return volatility is not clear.

Researchers normally illustrate the impact of news on volatility through news impact curve (Bekaert & Wu 2000). A news impact curve allows to plot the relationship between conditional volatility and shocks of either sign. It also allows to reflect asymmetric effects of shocks on conditional volatility. Pegan and Schwert (1990) use the news impact curve to compare various asymmetric models and Engle and Ng (1993) state that asymmetry effect is different across models.

Figure 1 shows the effect of firm-specific shocks (idiosyncratic shocks) and the mechanism by which volatility feedback can lead to asymmetric volatility at the firm level. According to the CAPM, a firm is priced based on its contribution to market risk in a well-diversified portfolio, not its own idiosyncratic risk. News at the firm level only creates asymmetric volatility through changes in leverage because idiosyncratic risk is not priced. However, if it is possible to establish a link between firm-specific shocks and risk premium, through conditional covariance, the effect of volatility asymmetry should be stronger at the firm level. Bekaert & Wu (2000) find covariance asymmetry in leverage portfolios constructed from Nikkei 225 stocks.

3. Empirical Literature Review

3.1 Volatility Asymmetry across Equity Markets

Several studies also focus on volatility spillovers across different equity markets. Booth et al. (1997) research the volatility spillovers in Scandinavian equity markets using multivariate EGARCH model and find that spillovers are asymmetric in nature, bad news cause more volatility transmission than good news. Ng (2000) studies the magnitude and changing nature of volatility spillovers from Japan and the US to the six Pacific-Basin equity markets and finds that the impact of various regional and world market factors on volatility transmission is evident to the Pacific-Basin markets. Koutmos and Booth (1995) investigate price and volatility transmission across London, New York, and Tokyo equity markets, using multivariate EGARCH model. Their findings suggest that any bad news arriving from the last market to trade causes volatility spillovers to have much more pronounced in each market, meaning that increased volatility from bad news drives a given market volatility through spillover effect.

3.2 Volatility Asymmetry at the Firm Level

Although many empirical investigations show evidence of volatility transmission, asymmetric effects, and time-varying risk premia at the market level as well as across other financial markets [Goeij & Marquering (2002), Emenike (2017), Scruggs and Glabadanidis (2003), Adjei B. (2015), Yang and Doong (2004)] (bond and foreign exchange market), the finance literature also concentrates on the conditional volatility at the firm or portfolio level. In other words, several studies covering different markets examine how market conditional volatility affects the firm or portfolio level volatility and asymmetric effects. One of the extensive studies conducted by Bekaert and Wu (2000) investigates asymmetric volatility at the firm and market level by examining two competing explanations of asymmetry: leverage effects and volatility feedback effect. Using the Japanese stock market daily data, they find evidence of volatility feedback effect, which is pronounced at the firm level by strong asymmetry in conditional covariances and reject pure leverage

hypothesis. They further document that conditional betas do not reveal significant asymmetry. Hong et al. (2007) study asymmetries in stock returns by constructing portfolios in which they find strong evidence of asymmetries in conditional betas and covariances. Consistent with this finding, Braun et al. (1995) study conditional covariances of stock returns using EGARCH model, allowing market volatility, portfolio-specific volatility, and beta to respond asymmetrically. Using monthly data, they find substantial support of conditional volatility in both market and portfolio parts of returns and weaker support for the time-varying conditional betas. Leverage effects are also absent in conditional betas. In contrast, Cho and Engle (1999) find that news affects conditional betas of individual stocks asymmetrically when investigating whether a beta increases (decreases) with bad news (good news), as does volatility. They argue that stock price aggregation in the Braun et al. (1995) research fails to capture the cross-sectional variation and hence, leads to weaker results. They also argue that since the asymmetric effects are readily apparent in daily stock data, using monthly data explains previous researchers' inability to detect asymmetry effects. Using Finnish stock market daily data, Koutmos and Kniff (2002) study time varying betas and asymmetry by constructing five size-based equally weighted portfolios. Using asymmetric GARCH models, they find evidence of time variation in betas and beta asymmetry which explain the short-term dynamics of systematic risk. However, using constant correlation model (CCORR) to model conditional covariance, they end up with no significant covariance asymmetry across the portfolios.

Although his study is connected to time-varying risk premium for international assets, Mazzotta (2007) examines why (global) investors should value asymmetric conditional covariance in computing risk premium. He shows that an international investor who overlooks covariance asymmetry overestimates required returns for equities of the G4 countries and for the world market, on average. Since this thesis concerns about risk premium at the domestic level, there is, therefore, logical and intuitive understandings of why investors should value asymmetric conditional covariance when computing risk premia. Allowing asymmetry in covariance forecasts, Thorp and Milunovich (2007) compute optimal portfolio weights and a range of expected returns. They find that covariance forecasted from asymmetric models (GJR-ADCC) produces less risky portfolios than that from symmetric models (GARCH-DCC), therefore, benefitting

investor welfare. Their findings also suggest that a shift from symmetric to asymmetric forecasts in both variances and covariances significantly lowers realized portfolio risk.

Wu (2001) further examines the determinants of asymmetric volatility-leverage effect and volatility feedback effect- by developing an asymmetric volatility model in which the volatility feedback effect is found significant both statistically and economically. Motivated by Bekaert and Wu (2000) research, Dean and Faff (2004) investigate whether conditional covariance between stock and market returns is asymmetric in response to good and bad news in the context of Australian equity market. They find significant covariance asymmetry which can partly explain volatility feedback of stock returns and time-varying risk premium. Since Fama and French (1992) show evidence that static version of the CAPM is unable to explain cross-section of average returns, Jagannathan and Wang (1996) investigate the conditional CAPM to examine cross-sectional variation in average returns using NYSE and AMEX data. Allowing betas and market risk premium to vary over time, they document that the specifications underlying the conditional CAPM are able to explain the cross-section of stock returns rather well. Bollerslev et al. (1988) research conditional CAPM model with respect to the conditional covariance between asset return and market portfolio return and show that conditional covariance is time-variant and is a significant determinant of time-varying risk premia.

The existing literature also suggests that the volatility asymmetry is generally larger for market index returns than that for individual stocks [Andersen et. al (2001), Kim & Kon (1994)]. Consistent with this phenomenon, Bouchaud et al. (2008) investigate the leverage effect quantitatively and find that the negative correlation between return and subsequent volatility is much stronger for stock indices than that for individual stocks. They, therefore, propose a simple “retarded model” for stocks which alters between a purely additive and a purely multiplicative stochastic process.

Bekaert and Wu (2000) mention that leverage and volatility feedback effects happen simultaneously and that they often interact. Consistent with this phenomenon, Bollerslev et al. (2006) states that the two competing explanations for volatility asymmetry are difficult to distinguish using lower frequency data since the casual relationships of return-volatility might appear immediately. Using high-frequency five-minute S&P 500 future returns data,

they are able to trace the effects of both leverage and volatility feedback effect. Their results suggest a prolonged negative correlation between volatility and current and lagged returns and a strong contemporaneous return between high-frequency returns and their absolute value. Zhou (2016) investigates the interaction between return and volatility in the U.S. real estate market using high-frequency data. He finds that both leverage and volatility feedback effect exist and that leverage effect dominates the volatility feedback.

Since most of the existing studies use daily or longer return horizons, using high-frequency data to determine leverage effect requires careful estimation procedures. Ait-Sahalia et al. (2013) argue that since the leverage effect can be detected by estimating the negative correlation between asset return and its changes in volatility using high-frequency data, they find that the estimated correlation is zero instead of a strong negative correlation. They, therefore, call this phenomenon "leverage effect puzzle" and identify different asymptotic biases to examine, such as biases because of discretization errors, estimation errors, market microstructure errors, and smoothing errors in estimating spot volatilities. The study suggests that a novel approach to correct these errors is to employ bias correction method when using high-frequency data. Moreover, Wang and Mykland (2014) develop nonparametric estimation for a class of stochastic measures of leverage effect, which provides opportunity to predict future volatility using high-frequency data.

Bollerslev and Zhuo (2006) provide a simple theoretical framework to investigate the leverage effect, volatility feedback effect, and implied volatility forecasting bias using one-factor continuous time stochastic volatility by Heston (1993). They find that leverage effect is always stronger for implied than realized volatility whereas the volatility feedback effect depends on the underlying structural model parameters. Furthermore, implied volatilities provide downward biased forecasts of subsequent realized volatilities. Consistent with Andersen et al. (2001) findings, Carr and Wu (2011) show that S&P 500 equity index return represents negative correlation with its volatility. They propose three different economic channels, namely leverage effect, volatility feedback effect, and self-exciting behavior, contributing this correlation in which they attempt to disentangle the relative contribution of each channel. The self-exciting behavior which they define as the occurrence of a financial event often increases the chance of more such events to follow, thus raising the market volatility. Using S&P 500 options, their results reveal that the

volatility feedback shows itself in the variation of short-term options, while the leverage effect has its most impact on long-term options. The self-exciting behavior affects both short and long-term option variations.

The selection of proper empirical methodology is important for finding the leverage, and volatility feedback effects. Smith (2007) argues that the choice of empirical methodology or model specification leads previous researchers not to find significant volatility feedback effect. Developing a stochastic model to assess positive risk-return tradeoff, he shows that volatility feedback is economically significant, which explains daily and monthly stock return volatility. In addition, Kim et al. (2004a) investigate whether there is a positive relationship between stock market volatility and equity risk premium. Using log-linear present value framework under an assumption of Markov-switching market volatility, they show that the relationship between volatility and risk premium is always positive and economically large, supporting the existence of negative and significant volatility feedback effect.

Following Bekaert and Wu (2000), Bae et al. (2006) attempt to disentangle the two competing effects using Markov-switching (to capture volatility between regimes) and GARCH (to capture changes in volatility within the regimes). Their findings suggest that volatility feedback exists within the volatility regimes; when controlling for leverage effect, recurrent regime shifts indicate a negative correlation between return and subsequent volatility. Incorporating endogenous switching into a Markov-switching regression, Kim et al. (2004b) find that there is a positive trade-off between risk premium and future volatility. They also find substantial evidence of volatility feedback effect. Using FIEGARCH-M (fractionally integrated EGARCH) model to the daily data, Christensen et al. (2009) find a negative volatility-return relation which supports the notion of leverage effect, volatility feedback, or both. Furthermore, using a dynamic panel vector autoregression model, Ericsson et al. (2016) study the dynamic relationships among leverage, equity volatility, and volatility feedback effect at the firm level. They find a larger leverage effect on firms' equity volatility than documented by Christie (1982), which is economically significant. In contrast to equity volatility, Choi and Richardson (2016) assess the asset volatility in which they attempt to determine how much of a firm's equity volatility is due to financial leverage, risk-premia, time-varying asset volatility, and

so forth. They find that equity volatility is mostly explained by the firm's financial leverage, the lagged asset volatility of the market, and the lagged asset volatility of the firm.

More recently, the explanation for volatility asymmetry is viewed from behavioral perspectives. Pati et al. (2017) investigate return-volatility relation in the context of behavioral phenomenon, loss aversion. Using four different stock markets data at the daily and intraday level, they find a negative, asymmetric, and nonlinear relation between changes in volatility index and stock market returns. They further show that volatility asymmetry across India, Australia, Hong Kong, and UK can be explained by the loss aversion principle.

4. Methodology

Empirical studies in the asset pricing field employ various multivariate GARCH-in mean frameworks to examine the intertemporal interaction between risk and expected return. These models allow conditional second moments to influence conditional mean, resulting in a time varying risk premium. In order to model how conditional market volatility affects conditional volatility at the firm level and thus, the changing risk premium, we need to model conditional covariances. In particular, a model that takes into account asymmetry effects-asymmetric volatility leads to covariance asymmetry- is important in this case. Exponential GARCH (EGARCH) framework is considered as a well-known asymmetric specification which overcomes some of the estimation difficulties of other GARCH specifications. A simple extension of the EGARCH specification to a multivariate case is employed by many researchers [Koutmos (1996), Dean & Faff (2004), Cho & Engle (1999), Braun et al. (1995), Booth et al. (1997), Jane & Ding (2009)]. Nonetheless, other multivariate GARCH specifications, such as BEKK model, dynamic conditional correlation (DCC) model [Engle & Sheppard (2001)], asymmetric dynamic conditional correlation (Cappiello et al. 2006) model, GJR model, are used to capture asymmetry effects in conditional covariances [Bekaert & Wo (2000), Kroner & Ng (1998)]. Since a more recent study by Dean & Faff (2004) uses EGARCH model and finds support for volatility feedback effects, the thesis, therefore, intends to apply this framework to examine the same in the Finnish stock market.

Traditional regression-based models fail to capture the dynamic behavior of variance because one of the assumption in the classical OLS (ordinary least squares) method is that variance of the error terms is constant, that is, homoscedasticity. However, this assumption does not hold for time series data when error terms of one period is dependent on the last period. It has long been found that financial data exhibit such pattern [Orskaug (2009), Rossi (2004)]. The time-varying behavior of the financial data implies that volatility of an asset or market tends to cluster in high-volatility periods and low-volatility periods. In other words, financial markets exhibit volatility clustering, that is, large changes tend to be followed by large changes and the same for small changes. This phenomenon is typically found in the financial time-series data and often regarded as the heteroscedasticity. Time-varying mean, variances, and covariances based on the information currently available are

referred as the conditional mean, variances, and covariances, respectively. If these are time-invariant, i.e., constants, these are called unconditional moments. Then the expected value of squared deviations over the sample period is the traditional estimate of the asset volatility (Skregelid 2009). However, when heteroscedasticity exists in the financial time series, the OLS estimates are biased and inconsistent (Brooks 2008).

4.1 ARCH

Robert. F. Engle is the first to introduce a model that treats conditional heteroscedasticity as a function of past shocks. The model, called the Autoregressive conditional heteroscedasticity, has become very popular in the modern asset pricing literature and had enormous influence on further research around time-varying volatility models. For his contribution, Engle was awarded Nobel prize in Economic Sciences in 2003. The ARCH model allows conditional variances to change over time as a function of past errors. In other words, first residuals are obtained from the perceived regression equation and then the conditional variance is evolved as a function of past squared residuals since the expected value of residuals is zero, leaving only residuals squared. Following ARCH equation (4), y_t is the conditional mean, σ_t^2 is the conditional variance of the error terms, while in the right-hand side $x_{1t}, \ldots\ldots, x_{nt}$ represents exogenous and endogenous variables at time *t*. The weight β_n and α_1 for the squares of past error terms is estimated from the data to provide the best fit.

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} +, \ldots\ldots\ldots, +\beta_n x_{nt} + u_t \qquad (4)$$

$$u_t = \sigma_t . z_t \, , z_t \sim N(0,1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

The above equation (4) shows an ARCH (1) process, however, more lags are possible to include in the right-hand side. The ARCH order represents the number of lags to be taken into account in the estimation of conditional variance. Because the ARCH model suffers for the violation of non-negativity constraint and difficulty in determining appropriate number of lags, a generalization of the ARCH model is discussed below. However, a full

analysis and explanation of the ARCH model is beyond the scope of this thesis since it represents only the foundation in which other time series econometric models are based upon (see details Engle 1982).

4.2 GARCH

The generalized autoregressive conditional heteroskedasticity (GARCH) model proposed by Bollerslev (1986) is less likely to violate non-negativity, i.e., variance cannot be negative. Because in the real-world negative variance is nonexistent, the GARCH model allows past conditional variances in the current conditional variance equation in addition to the ARCH terms. In practice, GARCH (1,1) specification leads to a more parsimonious and easy to estimate the model because it enables users to capture many stylized facts such as volatility clustering, and thick tailed returns (Goeij & Marquering 2002). The conditional variance equation can be expressed in the equation as below.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, u_{t-i}^2 + \sum_{j=1}^{p} \delta_j \, \sigma_{t-j}^2 \qquad (5)$$

As can be seen, conditional variance σ_t^2 varies over time, dependent on the last squared residuals, $\{u_{t-1}^2\}_{i=1}^{q}$. A necessary condition for the non-negative conditional variance is justified when $\alpha_0 > 0$, $\alpha_i \geq 0$ for $i = 1, \ldots, q$; $\delta_j \geq 0$ for $j = 1, \ldots, p$. Furthermore, $\{u_t\}$ is assumed to be a stationary process only when $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \delta_j < 1$ is satisfied because variance have to be positive. As long as the assumption of stationarity holds, the long-run average variance converges to unconditional variance, which is given by:

$$\sigma_t^2 = \frac{\alpha_0}{1 - (\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \delta_j)}$$

If $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \delta_j > 1$, the unconditional variance of $\{u_t\}$ is not defined and termed as non-stationarity in variance (Brooks 2008). The GARCH (p,q) as suggested by Bollerslev (1986) can be viewed as an Autoregressive Moving Average (ARMA) for the conditional

variance. In application, the most popular GARCH form is GARCH (1,1) where both p and q are equal to 1.

4.3 EGARCH

An important shortcoming of the GARCH model is that shocks of either sign have the same effects on conditional variance (volatility) which is not true due to the fact that asset prices at all times respond asymmetrically to shocks (Tsay 2006). Put differently, negative shocks cause conditional variance to rise more than positive shocks of the same magnitude. Various econometric models have been proposed to account these effects of volatility asymmetry, such as EGARCH, GJR, TARCH. However, to capture volatility asymmetry this thesis employs the univariate conditional variance is in the form of Exponential GARCH (EGARCH). EGARCH model was proposed by Nelson (1991). The reason for choosing this model is that it performs better to capture asymmetry than GJR and logarithmic transformation guarantees that variances are non-negative (Goeij & Marquering 2002). Although many forms of the EGARCH model are possible, a simple representation of the model can be expressed in the following equation. Often EGARCH (1,1) process is used in the literature.

$$ln\,(\sigma_t^2) = \alpha + \delta\, ln\,(\sigma_{t-1}^2) + \theta\, z_{t-1} + \gamma[|z_{t-1}| - E|z|] \qquad (6)$$

The term $\gamma[|z_{t-1}| - E|z|]$ measures the size or magnitude effect of an innovation whereas $\theta.z_{t-1}$ measures the corresponding sign effect. z_{t-1} is the standardized residual, which is defined as $\varepsilon_{t-1}/\sigma_{t-1}$, and $E(|z|)$ is the expected absolute value of z. δ measures the persistence of volatility and is related to the market conditional variances at time *t-1*. The model also accounts for asymmetry through the parameter θ. When θ< 0, $ln\,(\sigma_t^2)$ tends to rise (fall) following the negative market shock z which drops (rises) in prices. If γ> 0, the $\gamma[|z_{t-1}| - E|z|]$ term raises (lowers) $ln\,(\sigma_t^2)$ when the magnitude of a market shock is larger (smaller) than expected. Taken together, the term $\theta.z_{t-1}$ and $\gamma[|z_{t-1}| - E|z|]$ allow the market conditional variance to respond asymmetrically to positive and negative returns.

4.4 Multivariate Volatility Models

Although a vast majority of researches in the early decades were concentrated on the univariate volatility modeling, it is imperative to consider multivariate volatility estimation and forecasting because movement in one market of either direction considerably influences the movement of the other. In other words, financial volatilities of a given market or asset move in tandem with other markets or assets. In case of asset pricing, it depends on the covariance of the assets in the portfolio. In addition, if financial volatilities move and influence across markets or assets, the benefits of diversification from the construction of a well-diversified portfolio have virtually been squeezed. Therefore, understanding and recognizing this feature through a multivariate approach have substantial implications to make better decisions in various areas, such as asset pricing, portfolio selection, hedging and derivatives.

Multivariate models, for example, MGARCH model helps in the estimation and forecasting of covariances and correlations that are time-varying in nature (Brooks, 2008). A growing body of studies implement MGARCH or family of multivariate models for the purpose of investigating volatility transmissions, spillover effects, and asymmetries across markets and/or stocks [Booth et al. (1997), Ng (2000), Koutmos and Booth (1995)]. Conditional correlations based on past available information are usually estimated using the constant conditional correlation model of Bollerslev (1990) to make the ease of estimation. However, assuming constant correlation is not realistic and has no theoretical justification (Cappiello et al. 2006). Therefore, a model that does not make such assumption is definitely a better choice and have significant implications in decision support. Engle and Sheppard (2001) introduce the dynamic conditional correlation (DCC) where the correlations between assets are time-varying. Further, Cappiello et al. (2006) extend the DCC model to the asymmetric DCC (ADCC) model which allows us to capture asymmetries in conditional correlations. The benefit of CCC, DCC, and ADCC model over other multivariate models, such as BEKK model, is that they are based on the univariate GARCH process or other family of ARCH processes. This enables conditional covariances between assets to be calculated based on the standardized residuals of the estimated univariate volatility models.

In this thesis, the central focus is on estimating time-varying covariances between market and stocks which also exhibits asymmetry, it is imperative to emphasize more on the ADCC model.

4.4.1 Models of Conditional Variances and Correlations

In the world of volatility modelling, one of the approaches is to model the conditional variances and covariances (correlations) instead of directly modeling the conditional covariance matrix (for details, see Orskaug 2009). The conditional covariance matrix is decomposed into conditional standard deviations and a correlation matrix as:

$$r_t = \varepsilon_t \qquad (7)$$

$$\varepsilon_t = H_t^{1/2} Z_t \qquad (8)$$

$$H_t = D_t R_t D_t \qquad (9)$$

Where r_t is $n \times 1$ vector of log returns of *n* assets at time *t*, $H_t^{1/2}$ is $n \times n$ matrix at time *t* such that H_t is the conditional variance of ε_t. $H_t^{1/2}$ can be obtained by Cholesky factorization of H_t. Z_t is $n \times 1$ vector of iid errors such that $E[Z_t] = 0$ and $E[Z_t Z_t'] = I$. Furthermore, $D_t = diag\ (\sqrt{h_{1t}}, \ldots\ldots, \sqrt{h_{nt}})$ is the conditional standard deviation matrix, and R_t is the correlation matrix. Models in this class can fall into two categories: ones with a constant correlation matrix and one's with a dynamic correlation matrix.

4.4.2 Constant Conditional Correlation (CCC)

The constant conditional correlation model proposed by Bollerslev (1990) assumes that the correlation is constant over time, i.e., $R_t = R$ with each individual series or asset follows univariate GARCH model to estimate conditional variances. Hence, it follows

$$H_t = D_t\ R\ D_t \qquad (10)$$

By construction, the correlation matrix, $R = [\rho_{ij}]$ is positive definite with $\rho_{ii} = 1, i = 1, \ldots\ldots, n$. The off-diagonal elements of the conditional covariance matrix, H_t, are given by:

$$|H_t|_{ij} = \sqrt{h_{it} h_{jt}}\, \rho_{ij}\, , i \neq j \qquad (11)$$

The process $\{h_{it}\}$ is modelled as univariate GARCH (conditional variances) shown in the following:

$$h_{it} = c_{i0} + \sum_{j=1}^{q_i} \alpha_j\, \varepsilon_{i,t-j}^2 + \sum_{j=1}^{p_i} \beta_j\, h_{i,t-j} \quad (12)$$

Where c_{i0} is a $n \times 1$ vector, α_j and β_j are diagonal $n \times n$ matrices. H_t is positive definite when the elements of c_{i0}, α_j, and β_j are positive, since R is positive definite. Though the model guarantees positive definiteness of the variance-covariance matrix, the major problem is that most of the time, constant correlation appears to be a very strong assumption. Studies reject this assumption that unconditional and conditional correlation is constant for most assets and markets [Tsui & Yu (1999); Tse (2000)]. Hence, a model that does not assume correlation matrix to be time-invariant is necessary.

4.4.3 Dynamic Conditional Correlation (DCC)

Engle and Sheppard (2001) propose the dynamic conditional correlation model, a generalization of CCC model by Bollerslev (1990). DCC makes the correlation matrix to be time-varying, R_t and H_t is positive definite if R_t is positive definite at each time point. Since the correlation matrix has to be inverted each time, t, during every iteration, the ease of numerically simple estimation is lost. Alike CCC, the covariance matrix, H_t can be decomposed into conditional standard deviations, D_t and a correlation matrix, R_t; both are time-varying.

Estimation of the DCC model follows two phases: in the first phase, each series or asset takes the form as the univariate GARCH process and in the second phase, the correlation

matrix is estimated using standardized residuals from the former phase [Emenike (2017); Orskaug (2009)]. Thus, DCC-GARCH (1,1) has been more prevalent in its use and acceptance. Though DCC-GARCH (1,1) has been extensively used and discussed in the literature, there are no shortcomings to use other ARCH processes (such as EGARCH, GJR) as the underlying conditional variance process as long as the error distribution satisfies stationarity conditions that ascertain the existence of unconditional variance (Orskaug 2009). Hence, this thesis employs the univariate EGARCH process in the first phase estimation followed by (A)DCC in the second phase estimation.

The estimation of the DCC-GARCH model follows:

$$r_t = \mu_t + \varepsilon_t$$
$$\varepsilon_t = H_t^{1/2}\, Z_t$$
$$H_t = D_t R_t D_t$$

As shown in equation (9), the elements in the diagonal matrix as the standard deviations from univariate GARCH models.

$$\boldsymbol{D}_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nt}} \end{bmatrix}$$

Where,

$$h_{i,t} = c_{i0} + \sum_{j=1}^{q_i} \alpha_j\, \varepsilon_{i,t-j}^2 + \sum_{j=1}^{p_i} \beta_j\, h_{i,t-j}$$

R_t is the correlation matrix of the standardized disturbances, z_t:

$$z_t = D_t^{-1} \epsilon_t \sim N(0, R_t)$$

Since R_t is the correlation matrix, it is symmetric

$$\boldsymbol{R}_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & \rho_{n-1,n,t} & 1 \end{bmatrix}$$

In addition, R_t has to fulfill some conditions. To ensure H_t is positive definite, R_t must be positive definite. Besides, the elements in R_t must be in the range of +1 and -1, according to the correlation definition. Therefore, to satisfy these conditions R_t is decomposed into:

$$R_t = Q_t^{*-1}\, Q_t\, Q_t^{*-1} \qquad (13)$$

$$Q_t = (1 - a - b)\bar{Q} + a\, z_{t-1} z_{t-1}^{'} + b\, Q_{t-1} \qquad (14)$$

Where $\bar{Q}$ is the average of the unconditional covariance matrices of standardized residuals, z_t.

$$\bar{Q} = \frac{1}{n}\sum_{i=1}^{n} z_t\, z_t'$$

The parameters a and b are scalars and they must satisfy conditions: $a \geq 0$; $b \geq 0$; and $a + b < 1$ to guarantee H_t to be positive definite. Since Q_t is the covariance matrix, Q_t^* is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal.

$$\boldsymbol{Q}_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{nnt}} \end{bmatrix}$$

To ascertain that correlation values lies between +1 and -1, Q_t^* rescales the elements in Q_t: $|\rho_{ij}| = \left|\frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}\right| \leq 1$. Furthermore, Q_t must be positive definite to ensure R_t to be positive definite (Orskaug 2009).

4.4.4 Asymmetric Dynamic Conditional Correlation (ADCC)

Although DCC-GARCH model has empirically been successful to make correlations time-varying, it overlooks an important phenomenon in the stock market, which is volatility asymmetry: negative shocks cause volatility to increase more than positive shocks of the same size. Hence, a model that accounts for asymmetry in the time-varying correlations is imperative. Cappiello et al. (2006) introduce the asymmetric version of the DCC-GARCH model, called asymmetric dynamic conditional correlation (ADCC) which allows to analyze the asymmetric response of conditional correlations based on the GJR threshold model [Cappiello et al. (2006); Emenike (2017); Shrestha (2004)]. Therefore, the ADCC-GARCH model allows leverage effects in the correlation structure and asset-specific news impact.

The DCC model represented in equation (14) has been modified to account for asymmetric effects and thus, the ADCC model can be expressed as:

$$Q_t = \left(\bar{Q} - A'\bar{Q}\,A - B'\bar{Q}\,B - G'\bar{N}\,G\right) + A'\,z_{t-1}\,z'_{t-1}\,A + B'\,Q_{t-1}\,B + G'\,n_{t-1}\,n'_{t-1}\,G \quad (15)$$

Where *A*, *B*, and *G* are $n \times n$ diagonal parameter matrices, and $n_t = I[z_t < 0] \circ z_t$. If the argument is true, it takes value 1 and 0 otherwise ($\circ$ is the Hadamard product, i.e., element-wise product). $\bar{Q}$ and $\bar{N}$ are the unconditional matrices of z_t and n_t, respectively. Furthermore, $\bar{N} = E[n_t\,n'_t]$ and alike $\bar{Q}$, its expectation is not feasible and hence, are substituted by sample analogous, such as $\bar{Q} = \frac{1}{n}\sum_{i=1}^{n} z_t\,z'_t$ and $\bar{N} = \frac{1}{n}\sum_{i=1}^{n} n_t\,n'_t$. The sample period exhibits asymmetric effect if it is found a significant $n \times n$ parameter matrix *G* [Alexios (2015), Emenike (2017)].

4.4.5 (A)DCC Model Estimation

The parameters of a (A)DCC-GARCH model can be estimated using three different distributions for the standardized residuals, z_t: multivariate Gaussian, multivariate Student's t- and multivariate skew Student's t-distribution. Since standardized residuals are

assumed to be normal (Gaussian), this thesis discusses only multivariate Gaussian distribution (see details for all three distributions Orskaug 2009).

4.4.5.1 Multivariate Gaussian Distribution

The log-likelihood function for $\varepsilon_t = H_t^{1/2}\, Z_t$ is:

$$L(\theta) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{n/2}|H_t|^{1/2}} \exp\{-\frac{1}{2}\varepsilon_t^T H_t^{-1}\varepsilon_t\} \qquad (16)$$

Where θ indicates the parameters of the model and is split into two groups: $(\emptyset, \psi) = (\emptyset_1, \ldots., \emptyset_n, \psi)$, where $\emptyset_i = (\alpha_{0i}, \ldots \alpha_{qi}, \beta_{1i}, \ldots. \beta_{pi})$ are the parameters of the univariate GARCH model for the ith asset return series, $i = 1, \ldots., n$. $\psi = (a, b)$ are the parameters of the correlation structure as in equation (14). By taking the logarithm of equation (16) and substituting $H_t = D_t\, R_t\, D_t$, we obtain the log-likelihood.

$$\ln\big(L(\theta)\big) = -\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + \ln(|H_t|) + \varepsilon_t^T\, H_t^{-1}\varepsilon_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + \ln(|D_t R_t D_t|) + \varepsilon_t^T\, D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t) -$$

$$\frac{1}{2}\sum_{t=1}^{T}(nln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + \varepsilon_t^T\, D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t) \qquad (17)$$

The correctly specified log-likelihood is difficult to estimate, and therefore, the (A)DCC model involves two phase parameter estimation. In the first phase, the parameter $\emptyset$ of the univariate GARCH models are estimated for each return series by replacing R_t with the identity matrix I_n in the log-likelihood. In the second phase, the parameter ψ are estimated using the correctly specified log-likelihood as in equation (17), given the parameter $\emptyset$ (see details Orskaug 2009). Using the quasi-maximum likelihood (QML) approach proposed by Bollerslev and Wooldridge (1992), conditional normality of the error terms yields consistent and asymptotically normal parameter estimates provided that conditional means and variances are correctly specified, even when errors are not conditionally normal (Braun et al. 1995). The estimates can be obtained by numerical methods using the BHHH optimization algorithm (Berndt et al. 1974).

4.5 Empirical Framework

Let $r_{m,t}$ and $r_{i,t}$ be the (demeaned) returns process on the market and on the individual firm stock *i* at time *t*.

$$r_{m,t} = \sigma_{m,t}.z_{m,t}$$

$$r_{i,t} = \sigma_{i,t}.z_{i,t}$$

Given in the asymmetry in the market conditional variance, assume that market conditional variance follows a univariate EGARCH (1,1) process for the market returns. That is,

$$ln\,(\sigma_{m,t}^2) = \alpha_m + \delta_m ln\,(\sigma_{m,t-1}^2) + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]$$

In addition, the market portfolio's expected excess return is the (constant) price of risk times the conditional variance of the market (Merton 1980)

$$E[r_{m,t}|\Psi_{t-1}] = \lambda_t\,\sigma_{m,t}^2|\Psi_{t-1} \qquad (1')$$

Referring to equation (2), the expected excess return on any stock or firm is the price of risk times the conditional covariance between the stock's return and the market.

$$E[r_{i,t}|\Psi_{t-1}] = \lambda_t\,cov(r_{i,t}\,, r_{m,t}|\Psi_{t-1})\ \forall\ i \qquad (2')$$

Using historical returns, it follows the equation (2´):

$$r_{i,t} = \lambda_t\,\sigma_{im,t} + \sigma_{i,t}.z_{i,t}$$

Where, $\lambda_t = \frac{E[r_{m,t}|\Psi_{t-1}]}{E[\sigma_{m,t}^2|\Psi_{t-1}]}$ is the conditional market price of risk. $\sigma_{im,t}$, the conditional covariance follows an ADCC-EGARCH (1,1) process. That is, the conditional covariance between market and stocks follows:

$$\sigma_{im,t} = H_t = D_t\,R_t D_t \qquad (8')$$

D_t is the diagonal matrix of standard deviations from univariate EGARCH models

$$D_t = \begin{bmatrix} \sigma_{m,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix}$$

and that univariate conditional variance takes the following process for the market and stocks, respectively.

$$ln\,(\sigma_{m,t}^2) = \alpha_m + \delta_m ln\,(\sigma_{m,t-1}^2) + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]$$

$ln\,(\sigma_{i,t}^2) = \alpha_i + \delta_i ln\,(\sigma_{i,t-1}^2) + \theta_i z_{i,t-1} + \gamma_i[|z_{i,t-1}| - E|z_i|]$ for stocks $i = 1, 2, \ldots, n$.

R_t is the conditional correlation matrix of standardized disturbances as described above.

$$R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Q_t)^{-1/2}\, Q_t$$

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'Q_{t-1}B + G'n_{t-1}n'_{t-1}G \quad (15')$$

A significant parameter estimate, G would reveal the asymmetry effects at the covariance level. The log-likelihood of equation (15´) can be decomposed more clearly into a volatility and correlation component (Alexios 2015).

$$= \frac{1}{2}\sum_{i=1}^{T}(N\, log\,(2\pi) + 2\log|D_t| + \varepsilon_t^T\, D_t^{-1}D_t^{-1}\varepsilon_t) - \frac{1}{2}\sum_{i=1}^{T}(z_t^T z_t + \log|R_t| + z_t^T\, R_t^{-1}z_t^T)$$

5. Data

Studies concentrate on firm level and market level conditional volatility and covariance often use the daily adjusted closing prices (daily returns) of data series of stock and market index [Dean and Faff (2004), Cho and Engle (1999), Campbell and Hentschel (1992)]. In addition, researchers sometimes construct portfolios at the firm level to estimate conditional volatility and covariance [Bekaert and Wu (2000), Braun et al. (1995)]. To study volatility asymmetry at the stock and market level, the study intends to use data of the OMX Helsinki 25 stock index and its constituents. The OMXH25 includes 25 blue-chip companies in the Finnish stock market. For this empirical analysis the study uses the daily closing prices (adjusted for dividends and splits) of 25 constituents from the Datastream (Datastream code:P-adjusted closing price) for the period between 1 January 2009 and 31 December 2017, totaling 2,340 observations if we count 260 trading days per annum. A more up-to-date and recent sample period is selected because other similar studies use older data. It is worthwhile to inspect whether latest data structure contains evidence of the feedback effect as found in older sample period. The sample period is also unaffected by the 2008 financial crisis since the crisis period lasted between 2007 and 2008.

For the market return, OMXH25 return series for the same period is used. Using daily data is rational in this sense that more recent studies demonstrate that both feedback and leverage effects are typically observable in higher frequency data, such as intraday 5-minute return (Bollerslev et al. 2006). Daily data is also a higher frequency and many studies were able to trace these effects [Bekaert and Wu (2000), Dean and Faff (2004), Campbell and Hentschel (1992)].

Daily returns are assumed to be continuously compounded (log returns) returns though some studies use simple returns (Cho & Engle 1999). Logarithmic returns are calculated as:

$$r_{i,t} = ln(\frac{P_t}{P_{t-1}})$$

Some studies demean returns by their unconditional mean [Braun et al. (1995), Cho & Engle (1999)]. This thesis models the excess daily return over the risk-free rate. Since the short-term risk-free rate is less than zero, the study assumes excess daily return is simply the daily log return series. Also note that, the final sample consists of 24 stocks since one stock was listed in the exchange in the middle of sample period and thus, eliminated from the sample period. As expected, the return series should exhibit skewness, leptokurtosis, autocorrelation, and heteroskedasticity.

As can be seen in Figure 2, the adjusted closing prices of OMXH25 Index are shown on the left and 24 constituents on the right. Focusing on the index price series, it is evident that subsequent to the 2008 financial crisis the overall market movement was an upward trend with noticeable fluctuations from 2011 to the late 2012 and again from 2015 to the mid of 2016. Correspondingly, of the 24 constituents most firms (except Nokia, Fortum, YIT, Outokumpu, Outotec, Telia company) exhibit upward capitalization even though price fluctuations are pronounced across this period, for example, firms like Metso, Cargotec, Kesko, and Konecranes represent much more fluctuations. When the overall market is rising, some of the underlying stocks perform poor relative to the market. For example, since Nokia possesses almost 60% of the market trading volume, the bearing trend unveils Nokia's positioning and competitiveness in the market and industry, in particular its cellular business was lost following the year of 2010. Overall, it seems that the market index underlying the firms demonstrate growth, an increased market capitalization from 1584 in 2009 to 3917 in 2017.

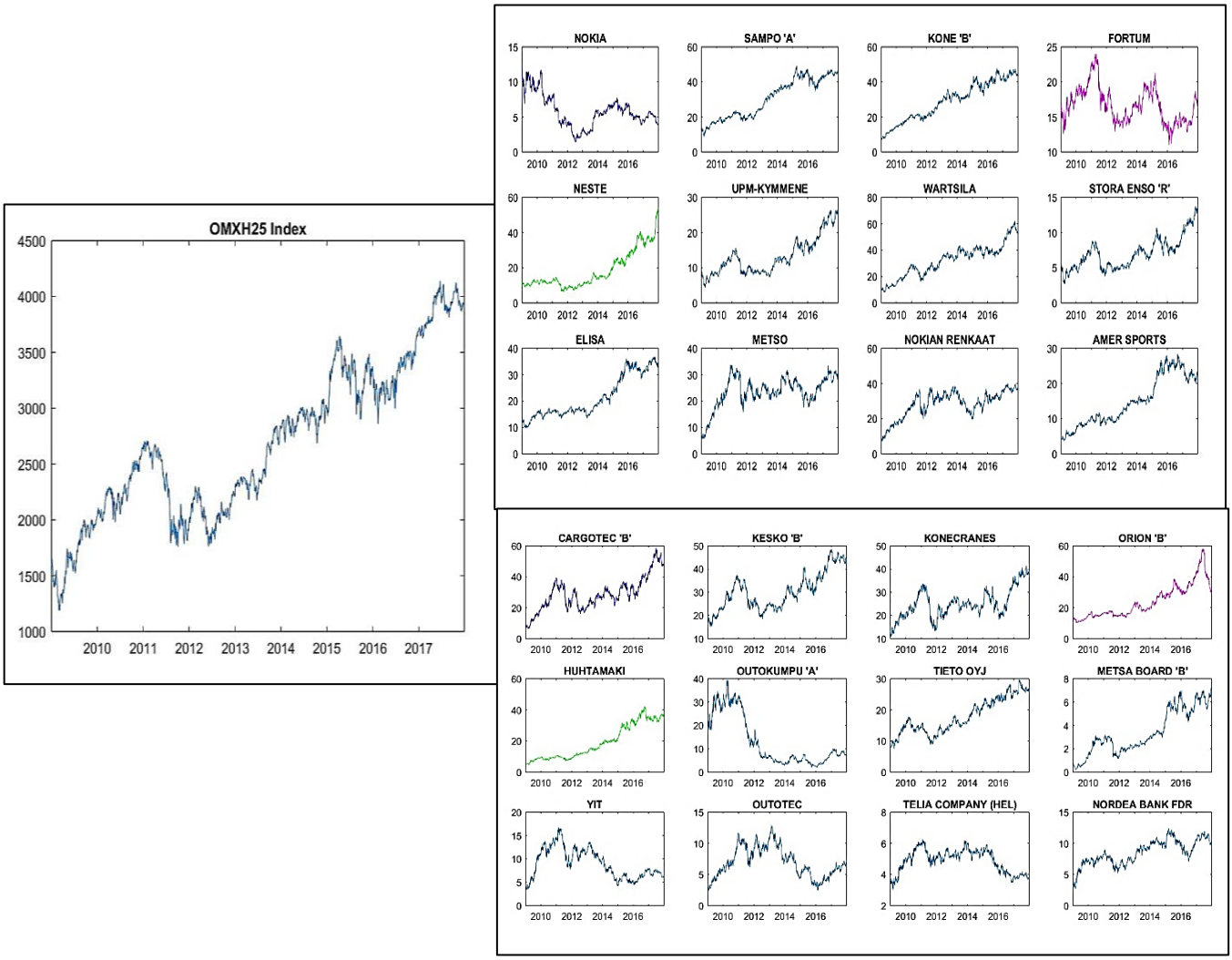

Figure 2: Daily Price series of OMXH25 and its constituents (x and y axis represent year and adjusted closing price, respectively)

5.1 Descriptive Statistics

Table 1 presents the descriptive statistics of daily returns series (%) for both the Index and constituents and reports mean, variance, standard deviation, minimum, maximum, median, kurtosis, and skewness. The dataset contains 2345 observations for each return series. The test

Table 1: Descriptive Statistics of Daily log return series (%) between 1 Jan 2009 and 31 Dec 2017

Descriptive Statistics of Return series											
	Mean	Variance	Median	Max	Min	Std. Dev	Kurtosis	Skewness	J_B	LBQ_{20}	LBQ_{20}^2
OMXH25Index	0.0386	1.8676	0.0093	7.98	-8.7509	1.3666	6.033	-0.1147	903.95	0.0211	0
NOKIA	-0.0456	7.0698	0	29.223	-19.609	2.6589	16.3151	-0.389	17382	0.142	0.0618
SAMPO	0.0519	2.3803	0.0272	10.181	-9.8685	1.5428	8.6952	-0.0725	3171.2	0.0007	0
KONE	0.0734	2.5588	0	11.434	-6.6673	1.5996	6.4333	0.1949	1166.6	0.0678	0
FORTUM	0.0029	2.5881	0	10.4	-14.182	1.6088	11.3508	-0.9246	7148	0.3942	0
NESTE	0.0669	4.4928	0	21.262	-12.187	2.1196	10.533	0.2416	5567.4	0.4012	0.0002
UPM-KYMMENE	0.0435	4.4848	0	12.364	-13.103	2.1177	7.2455	-0.1208	1766.8	0.0414	0
WARTSILA	0.0658	4.2134	0	13.042	-12.604	2.0527	8.0201	0.1605	2472.4	0.0995	0
STORA ENSO	0.0349	4.7278	0	12.01	-11.031	2.1743	5.2619	-0.0177	500.03	0.108	0
ELISA	0.039	2.0595	0.0453	7.0826	-10.889	1.4351	10.8892	-0.8891	6390.3	0.2418	0
METSO	0.0596	5.5404	0	17.753	-11.666	2.3538	6.8497	0.1815	1460.9	0.4042	0
NOKIAN RENKAAT	0.0653	5.1336	0	15.061	-12.612	2.2657	7.3098	0.2625	1841.8	0.1777	0
AMER SPORTS	0.0723	4.0667	0	12.027	-14.915	2.0166	10.0154	-0.2369	4830.8	0.0002	0
CARGOTEC	0.0705	6.1579	0	13.9	-14.955	2.4815	6.6747	-0.0485	1320.3	0.0012	0
KESKO	0.0394	3.0386	0	13.078	-13.736	1.7432	12.551	-0.2633	8940.2	0.0363	0.0076
KONECRANES	0.0473	5.0878	0	16.436	-10.375	2.2556	7.5702	0.5495	2158.8	0.3967	0
ORION	0.0384	2.6124	0.0263	14.247	-14.601	1.6163	15.3268	-0.5338	14958	0.1246	0.9935
HUHTAMAKI	0.0861	3.0684	0	12.114	-15.2	1.7517	9.8	0.2629	4545.1	0.0372	0
OUTOKUMPU	-0.0417	11.2665	0	19.792	-28.027	3.3566	7.6683	0.0532	2130.5	0.1867	0
TIETO OYJ	0.0495	3.492	0	13.596	-16.228	1.8687	10.4253	0.1633	5397.6	0.4987	0
METSA BOARD	0.0957	8.5077	0	24.696	-27.566	2.9168	17.0193	0.109	19208	0	0
YIT	0.0201	5.867	0	13.136	-12.8	2.4222	6.0081	0.0596	885.53	0.1871	0
OUTOTEC	0.0375	7.3946	0	14.81	-20.94	2.7193	7.0026	-0.2663	1593.1	0.3918	0
TELIA COMPANY	0	2.2126	0	7.8927	-9.4176	1.4875	7.0751	-0.226	1642.6	0.0001	0
NORDEA BANK FDR	0.0372	4.5193	0	14.036	-13.353	2.1259	9.2105	0.3065	3805.3	0.0005	0

statistics of Jarque-Bera test for normality and the p-value of Ljung-Box test for autocorrelation are also reported in the right side of Table 1. The mean indicates the average (expected) daily return percentage for the Index and each of the constituents. Having positive expected return is desirable for investors because of diversification benefits. However, Nokia and Outokumpu exhibit negative mean returns implying stock returns fall during the sample period, as it is also evidenced in the price series of each stock in figure 1: when the overall market is rising, stock Nokia and Outokumpu reflect the opposite behavior. Furthermore, the standard deviation is a measure of total risk (or volatility) and is calculated as the square root of the variance. The higher the standard deviation, the higher the risk. Outokumpu, Metsa Board, and Nokia represent the highest standard deviation in the sample period, 3.37, 2.92 and 2.66, respectively.

The Jarque-Bera (JB) test is used to test whether return time series are normal or not. Test for normality is important because it is often assumed that stock market returns are normally distributed, which is not true. In reality, stock returns tend to exhibit fat tails and excess kurtosis. The test is based on the fact that normally distributed data have a coefficient of zero for skewness and kurtosis coefficient lies below or equal to 3 (Brooks

2008). Referring to Table 1, column headed kurtosis, skewness, and J_B are used to test for normality assumption of the return series. In case of kurtosis, all series value are greater than 3 indicating that they have *leptokurtosis* which is a normal characteristics for time series data. In addition, most of the return series have negative skewness indicating that return series are not normal and that they are skewed toward left than normal. All other returns series whose skewness are not negative have skewness greater than 0, meaning that they are also non-normal and skewed toward right than normal distribution. Further, the JB test confirms the presence of non-normality in all return series at the 5% significance level. In other words, the null hypothesis of normally distributed data is rejected in favor of the alternative. It can be also observed that test statistic values of the JB test are greater than critical values and significant at the 5% level.

Moreover, the Ljung-Box test (simply LBQ) is used to test for autocorrelation in the return series. In table 1, it can be noticed under column LBQ_{20} and LBQ_{20}^2 that the p-values of the autocorrelation test indicate the strength at which the null hypothesis of returns are not auto-correlated are rejected. When return series are used, the LBQ test fails to reject the null hypothesis for more than half of the sample stocks. However, in case of squared returns, the test rejects the null hypothesis at the 5%, and 10% significance level, except the stock Orion where the test fails to reject. The autocorrelation test reveals the fact that how the mean return is affected by lagged values and that the rejection of the null hypothesis means that returns are serially correlated, implying the evidence of heteroskedasticity existence in the time series.

5.2 Tests for ARCH-type Models

Using financial time series data in ARCH family models requires some preliminary tests to ascertain that data is stationary, exhibit ARCH effects, and free from serial correlation. In addition, there must be the presence of volatility clustering in the financial data, meaning that a period of small changes tends to be followed by another period of small changes for a prolonged period, of either sign and period of large changes tends to be followed by another period of long changes for a prolonged period. This is to confirm that the use of ARCH family model is deliberately justified. To ensure that data is stationary, i.e., data

does not have unit root, Augmented Dickey-Fuller (ADF), Phillips Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are used. In addition, Engle ARCH test is used to ascertain that data contains the ARCH effect. The Ljung-Box Q test is used to see whether data is free from serial correlation as discussed before.

The ADF test is first used to examine whether data contains unit root. The null hypothesis for the test states that variable is non-stationary. Therefore, the rejection of the null hypothesis in favor of the alternative hypothesis of stationarity is desirable. To reject the null hypothesis, the test statistic is compared with the critical values and where the t-statistic is greater than the critical values in absolute terms at the 1%, 5%, and 10% significance level, the null hypothesis is rejected. As shown in Table 2, the t-statistic of all assets including the index is greater than the corresponding critical values at the 1% significance level implying that all return series are stationary during the sample period. Besides, the PP test is used to examine stationarity of the return series. Alike the ADF test, the null hypothesis of the PP test states that series is not stationary. Thus, the rejection of the null hypothesis in favor of the alternative of stationarity is desirable if the t-statistic is greater than the critical values in absolute terms at the 5% significance level. As can be seen in Table 2, the test rejects the null hypothesis at the 1% significance level and thus, all return series exhibit stationarity. To further confirm the stationarity issue, the KPSS test is employed to examine the same. The null hypothesis of the test is that series are stationary while the alternative hypothesis states that series has unit root. To affirm that the null hypothesis is not rejected, the t-statistic should be smaller than the critical values for all return series. In our case, as shown in Table 2, the test cannot reject the null hypothesis and thus, indicating all return series are stationary (see Appendix I shows all return series).

As mentioned, financial time series depicts volatility clustering or pooling- first introduced by Mandelbrot (1963)- is one of the basic attributes that trigger to employ nonlinear models. It simply describes that returns are far more dispersed during high volatility period as compared to low volatility period (Taylor 2011). In case of OMXH25 index and its constituents, there is also evidence of volatility clustering as shown in Appendix I. The original return series together with variances are plotted and it can be noticed in all series that high volatility causes high next-period volatility and so for the low changes in volatility. High period return volatility is visible during the beginning of 2009 to the end

which is possibly the effect of recent financial crisis. The market volatility also increased at the end of 2010 and persisted over a prolonged period till the end of 2012. During these periods, returns of either sign happened simultaneously. Similar volatility pattern can also be observed between 2015 and 2016. This phenomenon of volatility clustering exists in all return series and persists for a long period. In other words, the current level of volatility is correlated with the level of volatility during the past periods (Brooks 2008).

Table 2: Tests for ARCH-type models

	ADF	PP	KPSS	Engle_ARCH
OMXH25Index	-33.9456***	-47.1351***	0.0312***	225.2397***
NOKIA	-34.2183***	-47.674***	0.0974***	6.3762
SAMPO	-35.9245***	-48.5984***	0.0243***	189.2894***
KONE	-35.4864***	-49.1654***	0.0238***	90.4761***
FORTUM	-33.8478***	-47.5403***	0.04***	28.7756***
NESTE	-33.4403***	-48.7682***	0.0263***	23.5522***
UPM-KYMMENE	-32.9523***	-46.4556***	0.034***	53.4583***
WARTSILA	-34.6301***	-49.1074***	0.0231***	95.535***
STORA ENSO	-32.6188***	-46.0795***	0.0336***	126.9171***
ELISA	-34.7454***	-49.4794***	0.0392***	23.4968***
METSO	-34.0914***	-47.5704***	0.0865***	102.3712***
NOKIAN RENKAAT	-34.0781***	-47.8175***	0.0699***	112.2236***
AMER SPORTS	-34.4262***	-48.0818***	0.0238***	110.0451***
CARGOTEC	-33.4865***	-46.4028***	0.0734***	82.676***
KESKO	-35.1526***	-50.2023***	0.0525***	11.3689***
KONECRANES	-33.4159***	-46.5404***	0.055***	51.5064***
ORION	-34.2484***	-50.4152***	0.074***	5.1459
HUHTAMAKI	-34.4055***	-49.7013***	0.0486***	36.8343***
OUTOKUMPU	-32.7109***	-45.9653***	0.1089***	27.2216***
TIETO OYJ	-35.5224***	-50.8583***	0.041***	39.4221***
METSA BOARD	-31.3772***	-45.9581***	0.0572***	217.1577***
YIT	-34.3315***	-48.4782***	0.1387***	93.0676***
OUTOTEC	-33.2165***	-47.9266***	0.1177***	92.8909***
TELIA COMPANY	-35.9589***	-51.9214***	0.0204***	97.7554***
NORDEA BANK FDR	-35.6608***	-49.8093***	0.0278***	329.1585***

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

Furthermore, the Engle ARCH test is used to examine the presence of ARCH effects in the time series. Financial time series that exhibits conditional heteroskedasticity is said to have ARCH effects. Engle's ARCH test is a Lagrange Multiplier test to analyze the significance of ARCH effects. The null hypothesis of the ARCH-LM test states that there is no ARCH effect, i.e., no conditional heteroskedasticity while the alternative hypothesis is that there exists ARCH effect. As shown in Table 2, the test confirms the presence of ARCH effect in all return series at the 1% significance level except asset Nokia and Orion (whose p-value is greater than 10%). In all other cases, the null hypothesis is rejected.

The ARCH test reveals that Nokia and Orion demonstrate no ARCH effects. P-value (critical value) of Nokia and Orion is 0.27 (11.0705), and 0.40 (11.0705) respectively. Because the critical value falls above the test statistic of these two series, the test fails to reject the null hypothesis. In addition, failing to reject the null hypothesis when it is false is called type 2 error. That is, Nokia and Orion return series exhibit type 2 error for the ARCH-LM test. Since rest of the return series demonstrates ARCH effects at the 1% significance level, it is not surprising to find 2 series with no ARCH effects because the probability of 2 or more series failing the test (null of no ARCH) is low. Hence, it less likely that these 2 returns series with no ARCH effect affect hugely to the parameter estimation.

6. Empirical Results

This chapter concentrates on empirical analysis of the study and provides outcome for research questions introduced at the outset. The core part of the analysis is to examine asymmetric conditional covariances at the stock level, i.e., between market and stocks and its implications on time-varying risk premium. The analysis also encompasses volatility feedback effect, one of the two theoretical explanations for volatility asymmetry at the stock level. For the purpose of this analysis, volatility asymmetry is investigated with the DCC family models. The results obtained from the analysis are expected to provide investors to determine the time-varying risk and the premium for that risk. Before heading to the analysis, daily stock prices were converted to daily percentage returns and diagnostic tests for the data were carried out to ascertain the compatibility of the model chosen.

6.1 Market Variance

Table 3 reports parameter estimates of the market conditional variance estimated using univariate EGARCH (1,1) process. Market conditional variance is specified by demeaning market excess returns (i.e., excluding mean) as shown in the following. Table 3 presents all coefficient estimates along with t-statistic and p-value. P-value denotes the significance of the parameter and all parameter estimates are significant at 1% level. As discussed, coefficient δ_m measures the persistence of volatility and is related to the market conditional variance at time t-1. It is expected using daily return data that there is strong behavior of persistence in the market conditional variance as evidenced by significant lagged volatility coefficient, δ_m estimate of 0.99.

Table 3: Estimation of the EGARCH model on the Market Return

	Coefficient	t-statistic	p-value
α_m	0.0087	5.5212	0.0000
δ_m	0.9885	2861.655	0.0000
θ_m	-0.0847	-9.1873	0.0000
γ_m	0.1007	44.4129	0.0000
Loglikelihood	-3730.8360		

Note that market conditional variance is estimated using univariate EGARCH model by Nelson (1991). Daily return data for value-weighted market return between 1 Jan 2009 and 31 Dec 2017 are used. Parameters are estimated by maximum likelihood using the following specification:

$$r_{m,t} = \sigma_{m,t} . z_{m,t}$$

$$z_{m,t} \sim \text{N}(0,1)$$

$$ln\,(\sigma^2_{m,t}) = \alpha_m + \delta_m ln\,(\sigma^2_{m,t-1}) + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|].$$

$ln\,(\sigma^2_{m,t})$ is the natural logarithm of the market conditional variance. z_m is the standardized innovation of the market portfolio and is calculated as $r_{m,t}/\sigma_{m,t}$, where $r_{m,t}$ is the demeaned excess return on the market portfolio. Error terms are assumed to be Normal Gaussian distribution.

In addition, significant asymmetric volatility of market returns is evident. That is, asymmetric volatility in the market causes market return volatility to increase more than the volatility without asymmetry. As mentioned, the coefficients θ_m and γ_m together capture the asymmetric response of positive and negative return shocks to the market conditional variance. The coefficient estimates of $\theta_m = -0.0847$ and $\gamma_m = 0.1007$ are the evidence of significant volatility asymmetry at the market level. What happens in the market is that conditional variance increases more in response to negative market return shocks and unexpected large shocks than positive market return shocks and expected market return shocks. Hence, as expected, the evidence of significant volatility asymmetry at the market level is found. The figure named OMXH25 index in Appendix I shows the interactive behavior between estimated market conditional variance and market excess returns. Figure 3 plots the news impact curve for the market conditional variance. It is clear that market variance increases more when negative return appears and thus, further clarifying the substantial asymmetry effect in the market volatility.

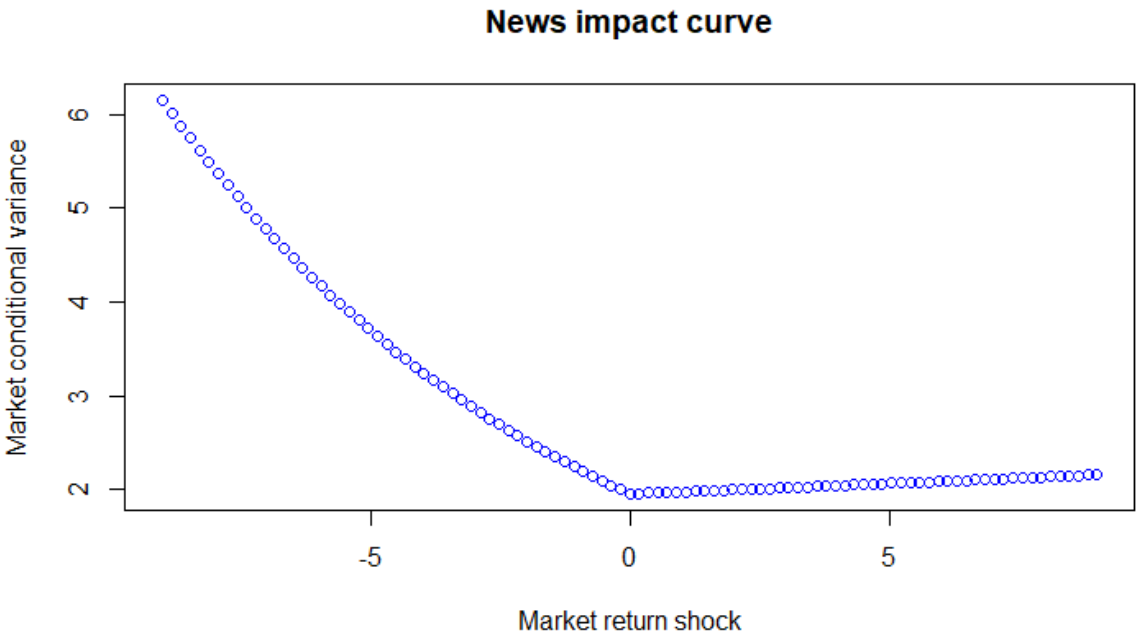

Figure 3: News impact curve for the market conditional variance

As it will be discussed in later sections, how the time-varying risk premium in the market is affected by the asymmetric behavior of market volatility in response to positive and negative return shocks.

6.2 Stock Conditional Covariance

Table 4 below reports estimation results of the conditional covariances of each 24 stocks. First note that demeaned log returns for both market and stocks are used to produce conditional covariances. There are 4 parameters in each conditional variance equation and 3 parameters in the Q_t process for conditional covariances, thus, 7 parameters in total in case of a bivariate estimation. As noted earlier, the asymmetry effect on covariances is captured by θ_m and γ_m in the market, θ_i and γ_i in the stock, and G in case of joint asymmetry. Parameters δ_m, and δ_i measure volatility persistence in the market and stock, respectively while the combined persistence effect is captured by parameter B. Table 4 below presents results of the estimation, parameter estimates, and t-statistics reported in the parenthesis. The log-likelihood for each stock is reported under column headed log on the right of the table.

Looking at the Panel A in Table 4, it can be noticed that univariate market conditional variance discussed above (in Table 3) is also analogous for each sample stocks. That is, parameter estimates and t-statistics across the stocks resemble the univariate market conditional variance. Despite this resemblance, Panel A reports market conditional variance again because it is a simultaneous estimate for conditional covariance in a bivariate setting. Eliminating a part of the entire process distracts the simultaneous estimation procedure. Hence, it is not surprising in the sense that ADCC-EGARCH model estimates the underlying variance process specified first. In addition, estimates of the market conditional variance are significant across all stocks as it is also found before. Test-statistics reported in the parenthesis also indicate the significance of parameter estimates. To assess the relation between market shocks and covariance, the asymmetry term θ_m and γ_m is of primary interest. θ_m estimates of -0.0847 is negative for all stocks and significant at the 1% level. Furthermore, γ_m estimates of 0.1007 is positive for all stocks and also significant at the 1% level. The results suggest the fact that shocks at the market level have strong asymmetric effect on conditional covariance. That is, conditional covariance increases more following a negative market return shocks and goes down to a lesser extent following a positive market return shock. Besides, the autoregressive term, δ_m measures volatility persistence of the market on conditional covariance. δ_m estimates of 0.9885 indicates the effect of greater volatility persistence on conditional covariance and is significant at the 1% level across all stocks. Hence, it is found that market conditional variance has a substantial impact on conditional covariance because market volatility drives the conditional covariance which is a dominant factor for determining risk-return tradeoff at the firm level. When the market volatility behaves asymmetrically, the conditional covariance between market and stock exhibits asymmetry as well. This finding is also consistent with previous researches [Bekaert & Wu (2000); Dean & Faff (2004)]. Therefore, the study finds answer of the first research question that negative market shocks increase conditional market volatility and thus, conditional covariance. That is, conditional covariance responds positively to increases in market volatility at the firm level. The question unearths the fact that market-level volatility asymmetry influences the firm-level volatility through covariance, again indirectly supporting the fact that a firm should be

Table 4: ADCC-EGARCH (1,1) Model Estimation Results, Daily Individual Stock Data

	Panel A: Market Variance				Panel B: Stock Variance				Panel C: Joint Estimate			
Stock	α_m	δ_m	θ_m	γ_m	α_i	δ_i	θ_i	γ_i	A	B	G	Log
NOKIA	0.0087***	0.9885***	-0.0847***	0.1007***	-0.0009***	0.9996***	-0,0261***	-0.0078***	0.0000	0.7688	0,0197	-8617.69
	(3.80)	(1987.54)	(-8.02)	(17.21)	(-4.36)	(22.60)	(-4.30)	(-70.29)	(0.00)	(0.21)	(0.8)	
SAMPO	0.0087***	0.9885***	-0.0847***	0.1007***	0.0233***	0.9765***	-0.0510***	0.1205***	0.0159**(	0.9671***	0,006	-6844.84
	(3.80)	(1987.54)	(-8.02)	(17.21)	(5.93)	(1670.30)	(-2.82)	(6.10)	2.43)	(56.57)	(0.47)	
KONE	0.0087***	0.9885***	-0.0847***	0.1007***	0.0349***	0.9714***	-0.0404**	0.1424***	0.0189***	0.9646***	0.0099	-7172.88
	(3.80)	(1987.54)	(-8.02)	(17.21)	(8.76)	(2207.05)	(-2.18)	(5.77)	(3.42)	(71.27)	(0.71)	
FORTUM	0.0087***	0.9885***	-0.0847***	0.1007***	0.0345***	0.9707***	-0.0268	0.1245***	0.0180**	0.9661***	0.0000	-7542.90
	(3.80)	(1987.54)	(-8.02)	(17.21)	(5.24)	(2104.13)	(-1.56)	(3.62)	(2.25)	(44.69)	(0.00)	
NESTE	0.0087***	0.9885***	-0.0847***	0.1007***	0.0336***	0.9814***	-0.0075	0.0706***	0.012	0.8924***	0.0836**	-8318.57
	(3.80)	(1987.54)	(-8.02)	(17.21)	(8.43)	(8211.47)	(0.43)	(16.54)	(0.74)	(18)	(1.89)	
UPM-KYMMENE	0.0087***	0.9885***	-0.0847***	0.1007***	0.0998	0.9385***	-0.0713	0.1363	0.0289	0.8455***	0.0479	-7758.35
	(3.80)	(1987.54)	(-8.02)	(17.21)	(0.22)	(3.21)	(-0.56)	(0.33)	(0.95)	(20.28)	(1.25)	
WARTSILA	0.0087***	0.9885***	-0.0847***	0.1007***	0.011***	0.9946***	-0.0409***	0.0435***	0.0573**	0.7913***	0.0212	-7700.89
	(3.80)	(1987.54)	(-8.02)	(17.21)	(7.89)	(19333)	(-3.99)	(12.15)	(2.10)	(9.27)	(0.47)	
STORA ENSO	0.0087***	0.9885***	-0.0847***	0.1007***	0.018***	0.9895***	-0.0367***	0.0642***	0.0138	0.9473***	0.0132	-7677.76
	(3.80)	(1987.54)	(-8.02)	(17.21)	(10.45)	(8554.01)	(-3.94)	(10.34)	(1.17)	(18.43)	(0.71)	
ELISA	0.0087***	0.9885***	-0.0847***	0.1007***	0.0387***	0.9579***	-0.0319	0.0922***	0.015**	0.9618***	0.0113	-7481.48
	(3.80)	(1987.54)	(-8.02)	(17.21)	(77.05)	(5370.69)	(-1.45)	(3.39)	(1.97)	(112.17)	(0.88)	
METSO	0.0087***	0.9885***	-0.0847***	0.1007***	0.0419***	0.9787***	-0.0543***	0.123***	0.0163**	0.9795***	0.0000	-7998.52
	(3.80)	(1987.54)	(-8.02)	(17.21)	(5.95)	(323.95)	(-3.62)	(3.96)	(2.32)	(87.48)	(0.00)	
NOKIAN RENKAAT	0.0087***	0.9885***	-0.0847***	0.1007***	0.0114***	0.9956***	-0.05***	0.0704***	0.0054	0.9636***	0.0215	-8152.98
	(3.80)	(1987.54)	(-8.02)	(17.21)	(6)	(5.30)	(-4.31)	(2.56)	(0.91)	(4.96)	(1.28)	
AMER SPORTS	0.0087***	0.9885***	-0.0847***	0.1007***	0.0715	0.9577***	-0.0406	0.199*	0.0135*	0.952***	0.0258	-8048.75
	(3.80)	(1987.54)	(-8.02)	(17.21)	(0.81)	(15.17)	(-1.48)	(1.68)	(1.78)	(39.28)	(1.16)	
CARGOTEC	0.0087***	0.9885***	-0.0847***	0.1007***	0.016***	0.9928***	-0.0229**	0.0463***	0.0386	0.8073***	0.0425	-8373.84
	(3.80)	(1987.54)	(-8.02)	(17.21)	(10.98)	(44765.5)	(-2.41)	(18.82)	(1.54)	(11.57)	(1.33)	
KESKO	0.0087***	0.9885***	-0.0847***	0.1007***	0.009***	0.9961***	-0.0233**	0.045***	0.0034	0.6232	0.0917	-7858.15
	(3.80)	(1987.54)	(-8.02)	(17.21)	(5.05)	(22588)	(-2.06)	(11.55)	(0.17)	(1.42)	(0.94)	
KONECRANES	0.0087***	0.9885***	-0.0847***	0.1007***	0.01***	0.9953***	-0.0434***	0.0389***	0.0149	0.8791***	0.0629**	-8126.61
	(3.80)	(1987.54)	(-8.02)	(17.21)	(7.29)	(12224.3)	(-4.55)	(6.57)	(1.03)	(15)	(2.08)	
ORION	0.0087***	0.9885***	-0.0847***	0.1007***	0.0541***	0.9504***	-0.062***	0.0531***	0.0279	0.9359***	0.0036	-7832.63
	(3.80)	(1987.54)	(-8.02)	(17.21)	(9.61)	(341.35)	(-2.89)	(6.10)	(1.57)	(25.54)	(0.17)	
HUHTAMAKI	0.0087***	0.9885***	-0.0847***	0.1007***	0.0618	0.9557***	-0.0718*	0.1562	0.014*	0.9678***	0.0146	-7808.61
	(3.80)	(1987.54)	(-8.02)	(17.21)	(0.60)	(11.02)	(-1.88)	(1.43)	(1.71)	(31.23)	(0.63)	
OUTOKUMPU	0.0087***	0.9885***	-0.0847***	0.1007***	0.0071***	0.9978***	-0.0272	0.0501*	0.0272*	0.9326***	0.0104	-9274.88
	(3.80)	(1987.54)	(-8.02)	(17.21)	(3.69)	(4844.82)	(-2.86)	(1.74)	(1.67)	(17.43)	(0.65)	
TIETO OYJ	0.0087***	0.9885***	-0.0847***	0.1007***	0.0409***	0.9749***	-0.0284	0.1226***	0.0000	0.9419***	0.0372*	-7978.46
	(3.80)	(1987.54)	(-8.02)	(17.21)	(6.75)	(774.54)	(-1.43)	(3.47)	(0.00)	(54.16)	(1.76)	
METSA BOARD	0.0087***	0.9885***	-0.0847***	0.1007***	0.0225***	0.9941***	-0.0356**	0.1136***	0.0432**	0.8711***	0.0000	-8573.21
	(3.80)	(1987.54)	(-8.02)	(17.21)	(4.17)	(4443.78)	(-1.99)	(5.17)	(2.02)	(21.57)	(0.00)	
YIT	0.0087***	0.9885***	-0.0847***	0.1007***	0.0336***	0.9836***	-0.0259*	0.091***	0.0526*	0.8128***	0.0289	-8375.54
	(3.80)	(1987.54)	(-8.02)	(17.21)	(11.97)	(9545.43)	(-1.77)	(24.61)	(1.86)	(13.09)	(0.61)	
OUTOTEC	0.0087***	0.9885***	-0.0847***	0.1007***	0.0267***	0.9882***	-0.0368***	0.078***	0.0131	0.9843***	0.0000	-8646.90
	(3.80)	(1987.54)	(-8.02)	(17.21)	(11.52)	(5131.73)	(-3.04)	(6)	(1.15)	(58.23)	(0.00)	
TELIA COMPANY	0.0087***	0.9885***	-0.0847***	0.1007***	0.0227***	0.9757***	-0.0414**	0.1081***	0.0354**	0.8466***	0.0622**	-7234.98
	(3.80)	(1987.54)	(-8.02)	(17.21)	(5.96)	(2156.88)	(-2.24)	(4.31)	(2.06)	(14.61)	(2)	
NORDEA BANK FDR	0.0087***	0.9885***	-0.0847***	0.1007***	0.0244***	0.9844***	-0.0516***	0.127***	0.0173***	0.9603***	0.0202**	-7580.51
	(3.80)	(1987.54)	(-8.02)	(17.21)	(7.03)	(765.91)	(-3.77)	(11.24)	(3.14)	(91.88)	(1.98)	
Averages	0.0087	0.9885	-0.0847	0.1007	0.0311	0.9792	-0.0395	0.092	0.0209	0.8984	0.0264	-7957.50
P values	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	

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

Note: the conditional covariance between market and stock is estimated using ADCC-EGARCH (1,1) process where estimation involves a two-stage process. First, the model estimates individual conditional variances (i.e., market conditional variance and stock conditional variance) using demeaned market return and stock return, expressed as r_t. Second, using standardized disturbances obtained from the first phase is used to make correlations time-varying, R_t through a Q_t process. Specification of the model is displayed in the following:

$$r_t = H_t^{1/2}.Z_t$$
$$H_t = D_t R_t D_t$$

D_t is the diagonal matrix of standard deviations from univariate EGARCH models

$$D_t = \begin{bmatrix} \sigma_{m,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix}$$

and that univariate conditional variance takes the following process for the market and stocks, respectively.

$ln\ (\sigma^2_{m,t}) = \alpha_m + \delta_m ln\ (\sigma^2_{m,t-1}) + \theta_m z_{m,t-1} + \gamma_m[|z_{m,t-1}| - E|z_m|]$.

$ln\ (\sigma^2_{i,t}) = \alpha_i + \delta_i ln\ (\sigma^2_{i,t-1}) + \theta_i z_{i,t-1} + \gamma_i[|z_{i,t-1}| - E|z_i|]$ for stocks i = 1,2,....,24.

R_t is the conditional correlation matrix of standardized disturbances.

$$R_t = diag(Q_t)^{-1/2}\ Q_t\ diag(Q_t)^{-1/2}\ Q_t$$

$$Q_t = (\bar{P}\ - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'Q_{t-1}B + G'n_{t-1}n'_{t-1}G$$

In relation to individual parameter estimates, the t-statistic is provided in parenthesis below the estimated value. The cross-sectional average for parameter estimates is reported in the end as well as the p-value for the cross-sectional t test for the hypothesis that the average parameter estimate is equal to zero reported below the average. The cross-sectional t-test for the average parameters is calculated as:

$T_{cross} = \sqrt{n}\ \frac{\mu_i}{\sigma_i}$

Where μ_i and σ_i is the cross-sectional mean, and standard deviation of the parameter estimates, respectively. T-statistics follows a t-distribution (two-tailed Student's t-distribution) with n-1 degrees of freedom.

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priced based on its contribution toward market risk (or volatility). The capital asset pricing model (CAPM) by Sharpe (1964) asserts that a firm should be priced by its systematic risk (measured by beta), not its idiosyncratic risk. However, idiosyncratic risk can only be priced if a firm changes its leverage. Because the risk of equity is proportional to the level of leverage a firm employs, leverage increases the equity volatility at the firm level (M&M 1958). Next, we will examine stock conditional variance for all stocks, which is important in the sense that how firm level volatility influences conditional covariance.

In contrast to the effect of market variance on conditional covariance, it is important to analyze how firm variances impact the covariance. Panel B of Table 4 shows the stock variance of each 24 sample stocks. Alike the market variance, the pertinent parameter estimates θ_i and γ_i capture the sign and size effect of individual stock excess return, respectively. Estimate of θ_i is negative across all sample stocks and significant for only 17

stocks. However, θ_i constitutes a cross sectional average of -0.0395 and is significant at 1% level. Besides, γ_m is positive for all stocks except Nokia and significant for all stocks but 2. Cross sectionally, γ_m averages 0.092 and is significant at 1% level. The significance of these parameter estimates indicates that shocks at the firm level have substantial asymmetric impact on conditional covariance. Put differently, idiosyncratic shocks cause covariance to increase more with negative return shocks than with positive return shocks. It further means that idiosyncratic shocks at the firm level influence the conditional covariance. Theoretically speaking, idiosyncratic risks are not priced unless it is caused by firm-level leverage. Because if leverage increases, the required return on firms' equity increases proportionally through changing covariance between market and firm. However, how idiosyncratic shocks increase covariance is the subject of leverage hypothesis which explains the reasoning for volatility asymmetry due to change in leverage at both the market and the firm level. Since this thesis particularly studies volatility feedback theory (i.e., time varying risk premium hypothesis), evidence for leverage effect has been detected in the parameter estimates. It is not surprising in the sense that leverage effect is easily found while investigating the volatility feedback since both of these effects derive from a single process. Hence, they might overlap each other. Studies by Bekaert and Wu (2000) investigate both leverage and feedback effect at the same time, while Dean and Faff (2004) study only the volatility feedback effect and document that they have not found any significant parameter estimates for idiosyncratic shocks. Back to parameter estimates, the autoregressive term, θ_i captures the effect of volatility persistence. It is found that θ_i averages 0.9792 and is significant for all stocks at the 1% level depicting that there is a strong persistence effect on conditional covariance. Thus, it appears that shocks at the firm level moderates the conditional covariance and need to be taken into account in determining the equity risk premium.

Panel C of the Table 4 shows the combined effects of both market and firm level shocks on conditional covariance. As mentioned earlier, parameter *B* measures the combined persistence effect and *G* captures the joint asymmetry effect on conditional covariance. The autoregressive term, *B* is found positive for all stocks and significant at 1% level (except Nokia and Kesko). The term averages 0.8984 and is also significant at the 1% level implying the fact that inherent volatility persistent effect from the market and firm also affects the conditional covariance. In addition, the term, *G* is positive for all stocks but

only significant for 5 of the 24 stocks. However, a cross sectional average of *G* is 0.0264 and significant at 1% level (by cross-sectional t-test). The cross-sectional t-test for coefficient *G* shows that test-statistics is greater than the critical value at the 1% significance level, thus, indicating that *G* is cross-sectionally significant (see Table 5 underneath). A positive coefficient value of *G* indicates the asymmetric behavior that negative return shocks at both the market and firm level have greater impact on conditional volatility than positive return shocks of the same magnitude. Although the level of combined asymmetric effect is minimal (according to the parameters' significance), it seems that shocks of any sign occurring at the firm and market level simultaneously affect the conditional covariance. This is intuitively appealing in the sense that market shocks together with firm-specific shocks drive market participants to change their expectations and equilibrium prices. Because idiosyncratic shocks should not be priced in an efficient market, only joint shocks of either sign should be priced. In contrast, it is found in the analysis that idiosyncratic shocks of either sign affect the conditional covariance and thus, questioning the efficiency in the market. Shaker (2013) finds that both the Finnish and Swedish stock markets are not weak-form efficient, implying that historical prices (returns) affect current stock prices (returns). This is also implied in the autocorrelation test in which returns are strongly autocorrelated.

Regarding the combined effect of shocks, the effect on conditional covariance is at its largest and positive when shocks of the same sign (i.e., both market and firm shocks are positive or negative) occur to the market and firm simultaneously. In other words, if both market and firm shocks are negative, conditional covariance appears to be the largest increase (see the news impact surfaces of covariance in Appendix II) and that causes the required return on stock to be higher to obtain equilibrium stock price. In contrast, when simultaneous shocks of the opposite sign (i.e., both market and firm shocks are positive and/or negative) happen to the market and firm, the impact on conditional covariance is negative and thereby, reducing the required return, and increasing the relative stock price. In other words, positive market shocks would moderate the effect of negative firm shocks, and negative firm shocks would moderate the effect of positive market shocks. This seems intuitive and theoretically appealing.

Overall, the results reveal the fact that shocks at the market level are important and priced by investors. Moreover, shocks at the firm level solely are not priced by market participants, at least theoretically. However, idiosyncratic shocks are found significant across sample stocks implying that investors consider them in determining the expected return. Idiosyncratic shocks should only be priced if it is caused by firm level leverage and this is what explained by the leverage hypothesis. However, this thesis does not test the leverage hypothesis explicitly. Furthermore, if leverage does not explain the idiosyncratic shocks at the firm level, then the efficiency of the market under analysis is in question. However, investors' price the joint effect of shocks which appear only through changing covariance when idiosyncratic shocks coupled with the market shocks occur simultaneously. The evidence of joint effect of shocks is minimal as few of the stocks are found significant.

Since conditional variance and conditional covariance were simultaneously estimated in the analysis, the outcome of asymmetric response of the conditional covariance is not strong enough as it has been found in the relevant parameter estimates. In other words, covariance does not exhibit strong asymmetric behavior given the market and firm shocks. However, the results were reverse in the study of Dean and Faff (2004) in which they show significant covariance asymmetry but insignificant volatility asymmetry at the firm level. Thus, our results provide weak support for the hypothesis that asymmetric behavior of market volatility observed is best explained using covariance asymmetry, and not firm-specific volatility asymmetry. Because the evidence of covariance asymmetry is not strong (only significant 5 of the 24 stocks), the required risk premium through changing covariance given shocks would not exhibit significant outcomes. Consequently, the time-varying risk premium theory (or volatility feedback) are less likely to reflect the required risk premium followed by the asymmetric response of conditional covariance. Covariance must respond asymmetrically in order to manifest the volatility feedback theory. However, recent research reveals the fact that volatility feedback effect largely prevails in the higher frequency data, such as intraday 5-min return (Bollerslev et al. 2006). Other researchers find that feedback effect is easily observed in market index return rather than in individual stock returns [Andersen et. al (2001), Kim & Kon (1994)] and that feedback effect together with leverage does not explain fully observed volatility asymmetry. Some researchers also argue that the selection of empirical model is important in detecting the volatility feedback

(Smith 2007) and others caution that some asymptotic error biases lead to poor results using higher frequency data (Ait-Sahalia et al. 2013). Considering all these facts and findings, the study next attempts to analyze the required risk premium investors require given the asymmetric behavior of conditional covariance.

7. Discussion

7.1 Economic Significance of Asymmetry

To examine the economic significance of volatility asymmetry implied by the parameter estimates, the effect of a standard return shock is examined. Additionally, averaging parameter estimates gives a useful idea of how covariance asymmetry impacts the expected risk premium. First and foremost, an estimate of the conditional market price of risk can be computed from the estimated model. The model estimates a market price of risk as a function of market excess returns and market conditional variance. That is, an average market price of risk can be calculated as:

$$\hat{\lambda} = \frac{1}{n}\sum_{t=1}^{n} \hat{\lambda}_t = \frac{1}{n}\sum_{t=1}^{n} \frac{r_{m,t}}{\widehat{\sigma^2_{m,t}}} = 0.009859461$$

The estimated market price of risk, 0.009859461 is used in equation 2 to obtain an estimated risk premium for the average stock. In other words, the average conditional covariance across 24 stocks is 1.7929 (see Appendix III), multiplied by the conditional market price of risk, 0.009859461, gives an estimated average risk premium of 4.60% per annum (assuming 260 days per annum). Test statistics of the estimated conditional covariance is reported in Appendix III. In the following, it is shown that the effect of a typical market and a firm shock on the estimated conditional covariance is examined and thus, affecting the expected implied risk premium.

Following Dean & Faff (2004) and Bekaert & Wu (2000), the value of a typical market shock is defined as the average of the absolute market standardized residuals from the estimation. That is, a typical market shock = $\frac{1}{n}\sum_{t=1}^{n} \left|z_{m,t}\right|$. Similarly, the value of a typical firm shock is defined as the average of the absolute firm standardized residuals from the estimation. That is, a typical firm shock = $\frac{1}{n}\sum_{t=1}^{n} \left|z_{i,t}\right|$. Once the standardized residuals for both market and firm are calculated, I simulate the original ADCC-EGARCH (1,1) model by specifying a positive market and/or firm shock i.e., the market and/or firm shock

calculated before. A negative market shock is provided by specifying a minus sign before market shocks and so does the same for firm negative shocks. Having simulated the model, the expected value of parameter estimates is compared to the average covariance. The analysis here is similar to the impulse response analysis often applied in Vector Autoregressive (VAR) to see the model dynamics given shocks. Table 5 summarizes the impact of these market and firm shocks on the conditional covariance and the resultant average risk premium.

Table 5: Economic Effects of shocks

	Panel A		Panel B			
	Market Shocks		Joint Impact of Shocks			
	+	-	**Market (+) Firm (+)**	**Market (-) Firm (+)**	**Market (+) Firm (-)**	**Market (-) Firm (-)**
Change in Covariance	-0.765	-0.907	-0.898	-1.082	-1.085	-0.946
Implied Risk Premium (% pa)	6.558	6.921	6.898	7.370	7.378	7.021
Change in RP (% pa)	1.962	2.325	2.302	2.774	2.782	2.425
% Change in RP	42.68	50.59	50.08	60.36	60.54	52.77

Note: this table shows the impact of a typical market and firm shock on the conditional covariance estimate, and the implied change in risk premium using average parameter estimates. Change in covariance is calculated as the difference between average conditional covariance (1.7929) and average conditional covariance with respect to the stated shocks. Average stock risk premium is calculated using the average conditional covariance over sample of stocks. The change in risk premium (change in RP (%pa)) is computed by deducting the average stock risk premium (4.60% pa) from the implied risk premium.

As it can be noticed in the above table, how the average stock risk premium is changed by the impact of asymmetric response of shocks on covariance. In other words, negative shocks have different impact on the average risk premium and that cause the risk premium to increase more than positive shocks. The last row of Table 5 shows the percentage change in risk premium and clearly demonstrates the impact of volatility asymmetry on the average stock risk premium, that is, how market (individually) and firm shocks (collectively) of either sign affect conditional covariance and thus, changing average risk premium.

Looking at the Table 5, it reveals that change in covariance is negative in all cases since average covariance (with shocks) is greater than the average covariance (without shocks). Panel A show how market level shocks by itself represent clear asymmetry in covariance

and risk premium. Both positive and negative shocks at the market level decreases covariance, however, their absolute magnitude is different. That is, a positive market shock decreases covariance by -0.77, increasing risk premium from 4.60% to 6.59%, an increase of 1.96%, and thus, a percentage increase of about 42.68%. It means that only positive news at the market level increases the average stock risk premium by 42.68%, other things held constant. In contrast, the effect of a negative market shock also decreases covariance more by -0.91 and increases risk premium from 4.60% to 6.92%. That is, it represents an increase of about 2.33% in the risk premium, a percentage increase of about 50.59%. It further means that only negative news at the market level increase the average stock risk premium by 50.59%. In other words, negative shock at the market level causes risk premium to increase more than positive shocks, increasing RP by an absolute amount of 7.91%. It seems plausible in the sense that both positive and negative market shocks increase the average risk premium, however, negative market shock increase more, implying that investors' demand higher required return and therefore, the stock price must fall at a level to reflect the equilibrium price. This shows only how the market-level shocks affect market risk premium and therefore, the expected stock premium must also change. Regarding the research question 2, it is found that negative market shocks increase market risk premium and thus, increasing the expected stock risk premium through changing covariance. Therefore, the asymmetry effect on the risk premium is evidenced when market negative shocks increase average stock risk premium more than market positive shocks.

The impact of firm-specific shocks (positive or negative) is not priced in an efficient market although firm-specific parameter estimates are found significant in the estimation. This is because the stock market is not efficient and/or there is some degree of firm-specific leverage, which can explain this phenomenon. Each of these mentioned reasons is beyond the scope of this thesis. Hence, the study expects that firm-specific shocks of either sign should appear through the joint impact of shocks.

Looking at the joint shocks impact of both market and firm, when firm and market level shocks are both positive, the effect on conditional covariance and risk premium is significant, with an increased risk premium of 2.30 points, producing a percentage increase of about 50%. In other words, positive news at both levels increases the average risk

premium from 4.60% to 6.90%. However, negative shocks at both levels are slightly different, generating a 2.43-point increase in the risk premium, representing a percentage increase of 52.77%. It can be noticed that the joint impact on the average risk premium given a negative shock is minimal. In other words, a negative shock at both market and firm level causes the average stock risk premium to increase by only an absolute amount of 2.77% more than that of a positive shock. It is not surprising in the sense that the joint impact of a negative shock is not much strong since the joint asymmetry term in the parameter estimates is mostly insignificant across sample stocks (only 5 of the 24 stocks are significant). It should have been more to reflect the strength of asymmetry effect on the risk premium. However, based on the amount of significant stocks, it is still worthwhile to note that asymmetry effects on conditional covariance and the average risk premium is clearly evident. Even though the asymmetry effect of a joint negative shock on the average risk premium is slightly higher (2.77%) than that of the corresponding effect of a joint positive shock, the increased risk premium, as a result of this, is considerable because the combined impact of a negative shock changes covariance. Hence, it can be deduced that bad news at both levels (market and firm) simultaneously increases the covariance risk such that the combined effect is considerable. Concerning the third research question's answer is conspicuous when negative shocks increase covariance risk and thus, the average stock risk premium increases more than corresponding positive shocks at both levels.

As can be seen in Table 5, the isolated effect of a typical market shock of either sign on the average risk premium is examined regardless of the corresponding isolated effect of a typical firm shock of either sign. This is because, first, in a world of CAPM, idiosyncratic shocks are not priced. Second, time-varying risk premium hypothesis embracing the conditional CAPM does not necessarily explain pure firm-level shocks. Third, pure firm-specific shocks only be priced if it is caused by firm-specific leverage and that is explained by leverage hypothesis. However, the leverage hypothesis is not under the investigation of this thesis. Although significant firm-specific parameter estimates imply firm-level leverage effect, the impact of a firm-level leverage effect on the average risk premium is beyond the scope of this study. Hence, the study does not explicitly examine the isolated effect of firm-level shocks, but only the joint impact of shocks.

The two other intermediate effects demonstrate some sort of asymmetry in conditional covariance and risk premium. Negative shocks at the market level and positive shocks at the firm level decrease conditional covariance by -1.08, an increased risk premium of 2.77 points, producing an increased risk premium of 60.36%. That is, the joint impact of a negative market shock together with a positive firm shock increases the average risk premium from 4.60% to 7.37%. In contrast, the joint impact of a market positive shock and a firm negative shock is slightly different. Positive shocks at the market level and negative shocks at the firm level decrease conditional covariance by -1.09, however, increase the risk premium by 2.78 points, representing an increased risk premium of 60.54%. It further means that the joint impact of a market positive shock and a firm negative shock increases the average stock risk premium from 4.60% to 7.38%, which is slightly higher. In other words, the combined effect of a positive market shock and a negative firm shock increases the average risk premium by 1 point (7.38% - 7.37%) more than that of a corresponding effect of a negative market shock and a positive firm shock. It seems that in case of a joint shock, a negative shock at the firm level increases the risk premium a bit more. This is not unexpected since firm-specific asymmetry term is found significant over sample stocks (17 of the 24 stocks) and thus, it is reasonable that firm-specific variances have some impact on the risk premium. Therefore, it suggests that positive market shock and negative firm shock cause the average risk premium to increase (by 1%) more than negative market shock and positive firm shock, which contradict with the fourth research question. Even though the difference in the average risk premium is small (1%), it shows the influence of a negative firm shock together with a market shock in estimating risk premium, that is, the impact of a negative firm shock is influential to some extent. It could have been more if the remaining sample stocks represented asymmetry in their parameter estimates. The fourth research question requires attention since it indirectly provides support for the CAPM. CAPM asserts that, in a world of asymmetry, pure negative shock at the firm level is not pronounced in the market, *ceteris paribus*. Because firms' stock is priced based on systematic risks, in case of a joint shock, a negative shock at the firm level is not supposed to have much influence in determining risk premium. However, this is not true in this case since it is found that negative firm shock together with positive market shock increases the average risk premium more than a corresponding negative market shock and positive firm shock. The reason of such impact is not subtle in the sense that it might be either caused by the market inefficiency or firm-level leverage. Either of these mentioned reasons requires

further investigation, however, it is established through researches that the Finnish stock market is not weak-form efficient. Recall that in an efficient market, idiosyncratic shocks are not priced by the market and investors' expectations about expected return of the stock only depend on the systematic risk. An efficient and equilibrium market setting is required in order to support the CAPM, which of course does not hold for small sized and emerging equity markets. Hence, the study cannot deliberately embrace an indirect empirical support for the CAPM with 100% certainty.

The analysis clearly shows that the risk premium is sensitive to return shocks, in particular, it is more responsive to the negative return shocks, for either market or firm, than positive return shocks. Negative return shocks cause the risk premium to increase more than positive return shocks, for either market or firm. It should be noted that these results are independent of the market price of risk since the market price of risk is a common factor used across all calculations.

7.2 Volatility Feedback

As mentioned earlier, the impact of joint asymmetry on the risk premium is minimal since the joint asymmetry term in the parameter estimates is mostly insignificant over sample stocks. However, firm-specific asymmetry term is found largely significant, which might explain some degree of leverage existing at the firm level. Of the 24 sample stocks, 17 show significant volatility asymmetry. Leverage hypothesis explains observed volatility asymmetry caused by leverage at the firm level. Although the study finds the evidence for leverage hypothesis, it does not explicitly account the amount of volatility asymmetry that can be caused by leverage. A further study should take this into account. However, this thesis studies only the time varying risk premium hypothesis (i.e., volatility feedback) which cannot account for fully fledged volatility asymmetry since only 5 of the 24 sample stocks show significant volatility asymmetry. Thus, the evidence for the volatility feedback is rather weak. In addition, the volatility feedback hypothesis cannot explain volatility asymmetry at the firm level since in a CAPM world, the systematic risk, i.e., covariance with the market, is priced, not idiosyncratic risk which according to the CAPM is not priced by well-diversified investors'. If firm level volatility asymmetry were explained by

the time varying risk premiums, then any increases in market volatility should cause covariance with the market to increase [Dean & Faff (2004), Bekaert & Wu (2000)].

It is worthwhile to investigate that whether firms which show significant volatility asymmetry at their own are significantly different from firms which exhibit only significant joint volatility asymmetry. A further investigation reveals that of the 5 stocks that show joint volatility asymmetry, 2 stocks show only joint volatility asymmetry without the effect of their own asymmetry. The other 3 stocks are inclusive, meaning that they exhibit asymmetry at their own and the joint asymmetry simultaneously. Recall that in theory, volatility asymmetry is explained by the leverage and volatility feedback hypothesis. Only if firms-specific observed volatility asymmetry is explained by the leverage hypothesis and joint volatility asymmetry by time varying risk premium hypothesis, then of the 24, 19 stocks can explain this observed volatility asymmetry. The remaining 5 stocks do not fall into this explanation for asymmetry and thus, their return-volatility behavior might be influenced by any extraneous forces. It seems plausible because many researchers document that the two hypotheses do not account fully fledged volatility asymmetry.

The results suggest that conditional covariance responds positively to increases in market volatility at the firm level. Firm level volatility is tied to the market volatility through conditional covariance. In addition, the asymmetric response of conditional covariance between market and stock returns is not much strong. This is because the joint asymmetry parameter estimates are mostly insignificant. Even though the impact of asymmetric behavior of covariance on the average stock risk premium is evident in the sense that negative return shocks cause the risk premium to increase more than positive return shocks, the incremental risk premium is not greater and not much strong. The impact of covariance asymmetry on the risk premium could be strong if the joint asymmetry term was significant in most of the stocks in that it responds more to negative shocks than to positive shocks. Hence, the fifth research question that volatility feedback is particularly strong when the conditional covariance is asymmetric is negative. This is because the results suggest that evidence for volatility feedback is rather weak. In contrast, studies by Bekaert & Wu (2000), Dean & Faff (2004), Bollerslev et al. (2006) find that volatility feedback is strong.

Regarding the leverage hypothesis put forward by Black (1976) and Christie (1982), the study does not test this hypothesis, however, finds reasonable evidence of leverage effects. Firm-specific asymmetry term is largely significant across the whole sample. This is not to say that volatility feedback hypothesis does not explain the observed volatility asymmetry. Of course, it does, however, the extent to how much volatility asymmetry each of these two hypotheses explain requires further investigation.

8. Conclusion

In this thesis, the asymmetric nature of conditional variance, covariance, and their impact on time-varying risk premium is examined. The study investigates observed volatility asymmetry at the firm level, which is explained by the time-varying risk premium hypothesis. Moreover, investigation for the observed volatility asymmetry at the firm level has greatly been emphasizing in the recent literature. Thus, for the purpose of analysis, the Finnish stock market, in particular OMXH25 index was chosen since no studies so far have attempted to investigate volatility asymmetry within the framework of time-varying risk premium theory. Since volatility varies over time and so does correlation between market and firms, it is important that investors need to revise the risk-return trade-off useful for portfolio diversification, asset allocation, and risk management.

The central part of this study is to investigate whether conditional covariance increases with negative shocks and decreases with positive shocks, as does conditional variance. The study employs daily log returns data for OMXH25 and its constituents from January 1, 2009 to December 31, 2017. The final sample includes 24 stocks since one stock was listed (in 2014) in between the sample period. To examine the asymmetric behavior of conditional covariance, the study uses ADCC-EGARCH (1,1) model. The reason for employing this specification is that asymmetries in the variance and covariance process can be craftily detected through this simultaneous estimation. In addition, the model has developed in a bivariate setting since asymmetry in conditional covariance between market and firm is the utmost concern.

The study finds that market volatility increases firm level volatility significantly through an increase in conditional covariance. The asymmetric nature of market volatility also increases conditional covariance substantially. Since all parameter estimates of conditional market volatility are significant, the study finds consistent evidence in regard to the first research question that conditional covariance responds positively to increases in market volatility at the firm level. In addition, it is found that firms-specific volatility considerably increases covariance because parameter estimates of conditional firm variance over the sample are largely significant. However, the conditional version of CAPM does not explain idiosyncratic variance in an efficient market since it assumes that investors' holding well-

diversified portfolios bear only systematic risk for which compensation is made. Moreover, idiosyncratic risks are not priced by investors in an efficient market unless it is caused by firm level leverage. Significant asymmetry term in firm-specific variance estimation indicates the existence of leverage effects and hence, a further analysis of leverage hypothesis coupled with time varying risk premium hypothesis is required. Only then the observed volatility asymmetry can be explained. Another plausible reason for significant idiosyncratic variances is that the market under analysis is not weak-form efficient, which has been brought out by recent empirical studies. A CAPM model which works better in an efficient and equilibrium setting might not adequately explain the risk-return dynamics of other inefficient markets. Whether it is for market inefficiency and/or firm level leverage can be determined only once the leverage and volatility feedback theory are simultaneously implemented.

The study examines that the observed volatility asymmetry can be explained by the time-varying risk premium through changing covariance, not through beta. Simultaneous estimation of the model produces the joint impact of shocks on conditional covariance. The study finds a weak support for asymmetric covariance since asymmetry term of the joint estimates are mostly insignificant. Given this weak evidence, the impact of asymmetric response of covariance on the average risk premium is impliedly evident. Negative return shocks of either market or firm increase the risk premium more than that of positive return shocks. Hence, the study finds answer in regard to the second question that negative shocks at the market level increase the market risk premium and therefore, expected stock risk premium. In case of a joint shock, the study finds that negative shocks at both levels increase the average risk premium slightly more than positive shocks at both levels simultaneously. Hence, the study finds answer regarding the third research question that negative shocks at both levels simultaneously increase covariance risk so that the combined effect is considerable. In addition, the study finds that negative firm shock together with positive market shock has slightly higher impact on risk premium than that of a corresponding negative market shock and positive firm shock, which contradicts with the fourth research question and thus, the indirect empirical evidence for CAPM is not found or requires further investigation if it is caused by leverage effect. The study also finds that the impact of joint asymmetry on the risk premium is minimal because the time-varying risk premium hypothesis cannot account for fully fledged volatility asymmetry since only 5

of the 24 sample stocks show significant volatility asymmetry. Thus, the evidence for the volatility feedback is rather weak. Instead the evidence for firm level leverage effects is evident and thus, strong. Hence, the study finds weak support for volatility feedback hypothesis of Pindyck (1984) which states that feedback effect is particularly strong when the conditional covariances between market and stock returns are asymmetric. In contrast, several other researchers e.g., Dean and Faff (2004) and Bekaert and Wu find strong feedback effect in the Australian and US equity market, respectively.

The results of this thesis have relevant implications to many: investors, practitioners, and researchers. Since return-volatility relationship is a crucial factor in the stock market, understanding how they work, and evolve over time improves our knowledge about their dynamic relationship. Investors become aware of the expected return from an asset when volatility increases, and responds asymmetrically, thus, enabling them to price the asset precisely. Practitioners such as portfolio managers can understand market volatility behavior that helps diversify portfolios in a way that reduces portfolio risk. Because volatility is not directly observable, its importance relates to many areas of finance: asset pricing, options valuation, and asset allocation. By knowing the results, researchers can further extend the scope of the research and investigate other equity markets to unearth the dynamism of volatility asymmetry.

The findings of this study contribute to further investigate the observed volatility asymmetry in the Finnish equity market. The future researches should embrace both leverage hypothesis and time-varying risk premium hypothesis to explain the volatility asymmetry, and its impact on the risk premium. It is interesting to further investigate how much volatility asymmetry can be explained by two of these competing hypotheses and the impact on risk premium.

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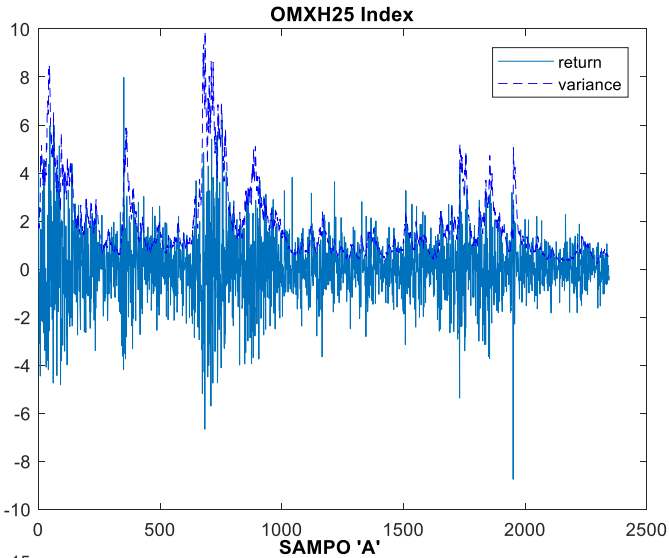
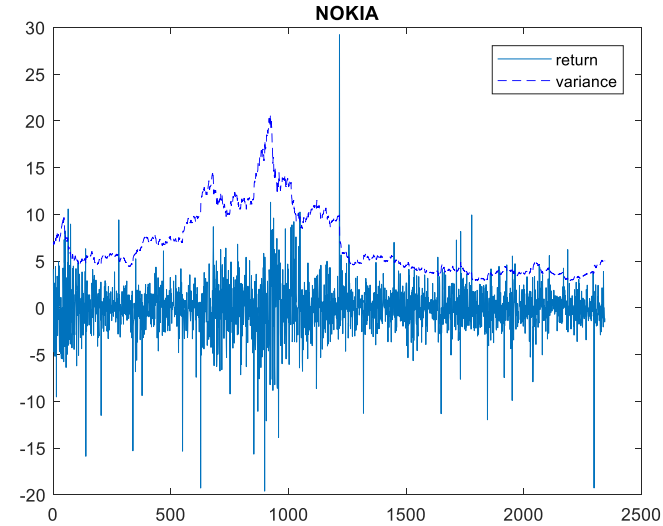
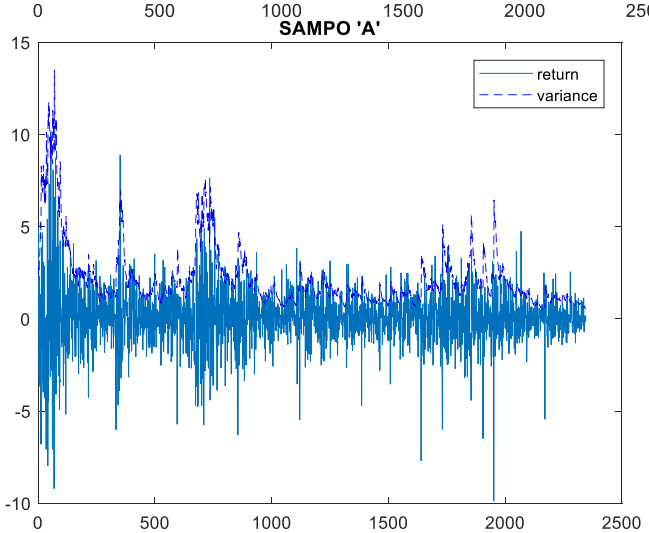
[1]@Manual{Ghalanos_2014, author = {Alexios Ghalanos}, title = {{rmgarch}: Multivariate GARCH models.}, year = {2014}, note = {R package version 1.2-8.}}

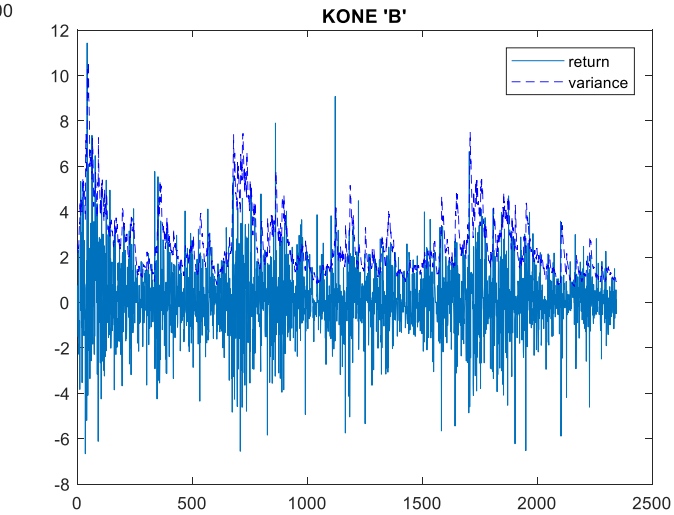
[1] Reference of the R-package used for analysis

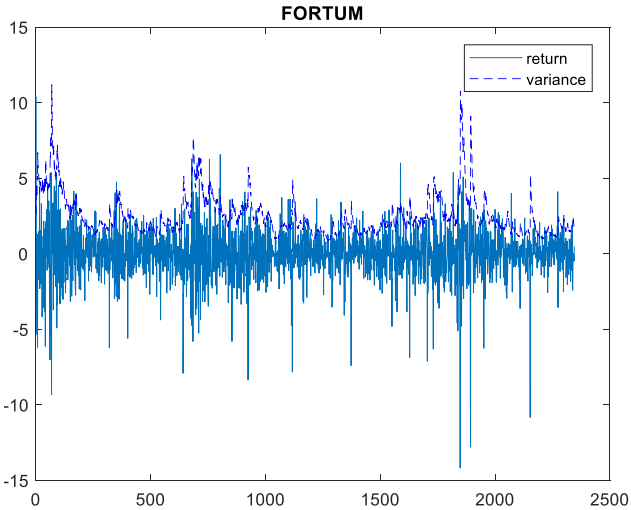
APPENDIX I: Volatility Clustering

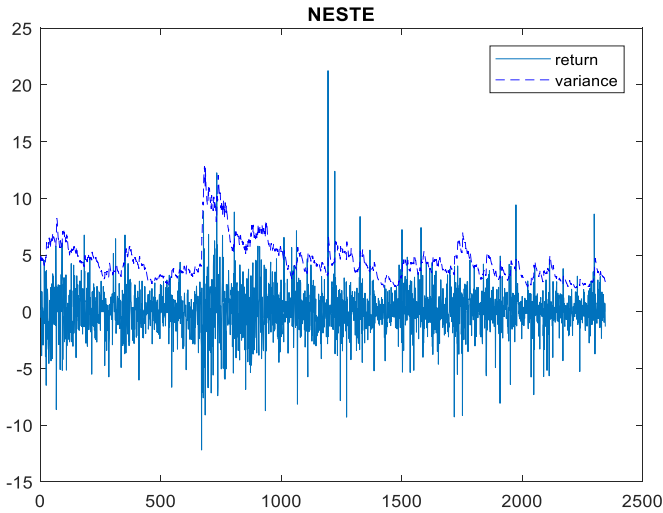


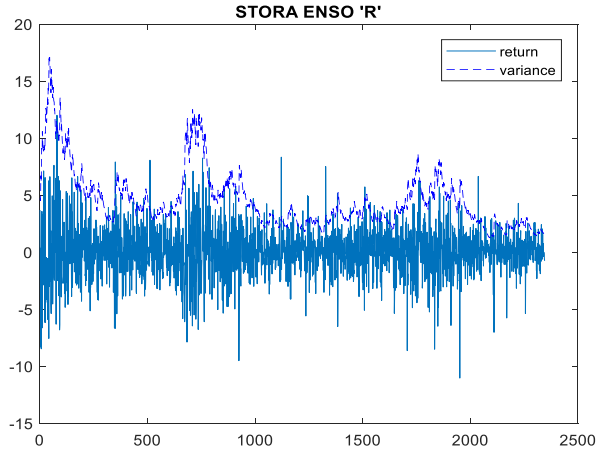


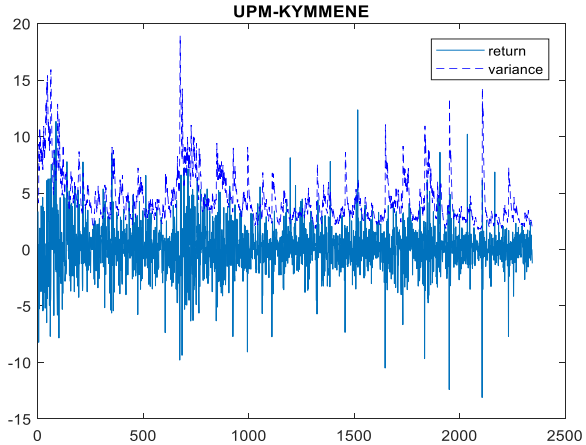


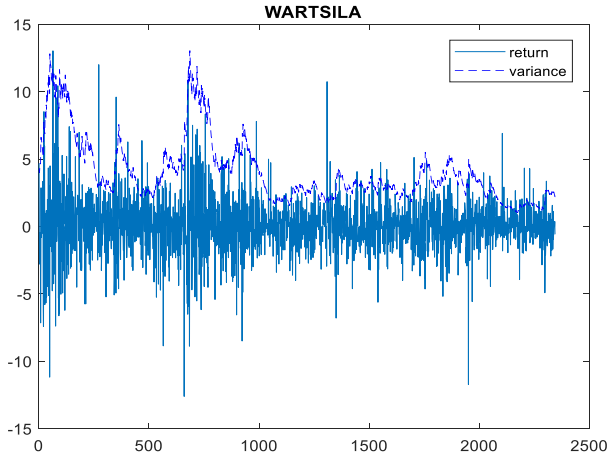


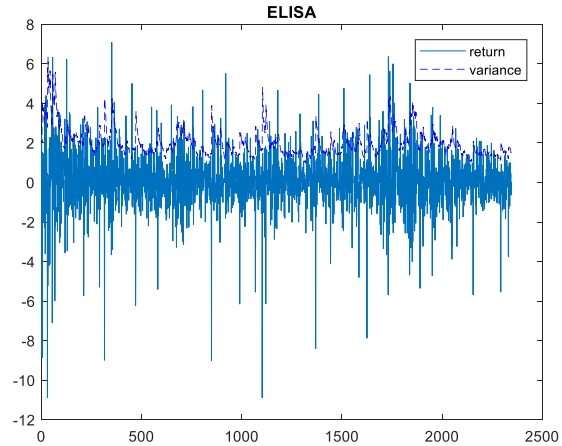


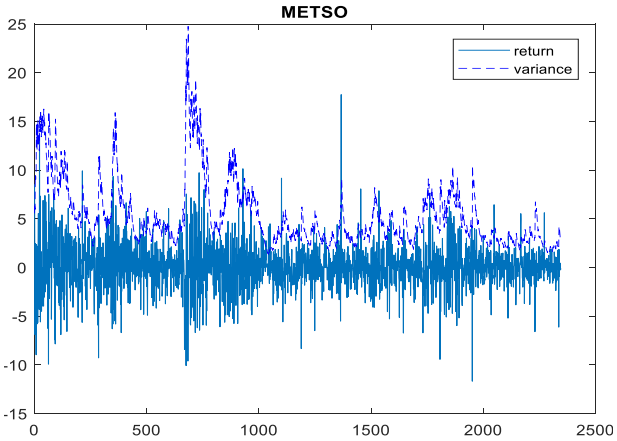


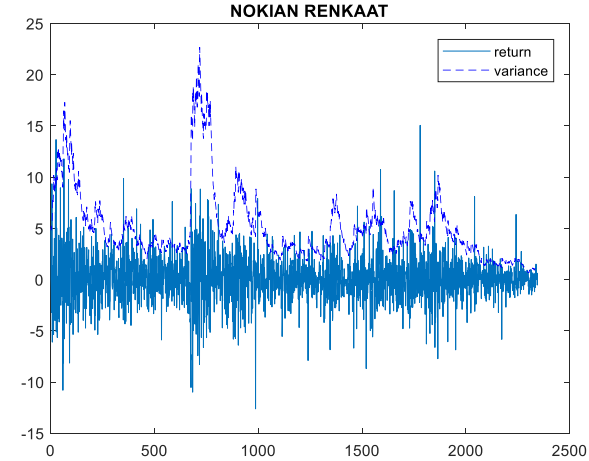

STORA ENSO 'R'
return
variance

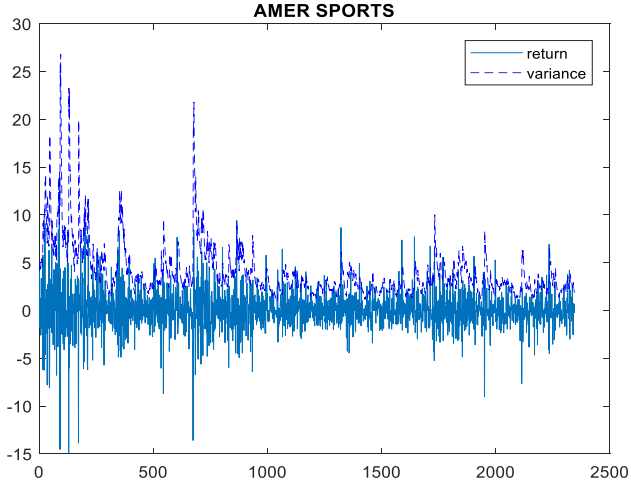

UPM-KYMMENE
return
variance

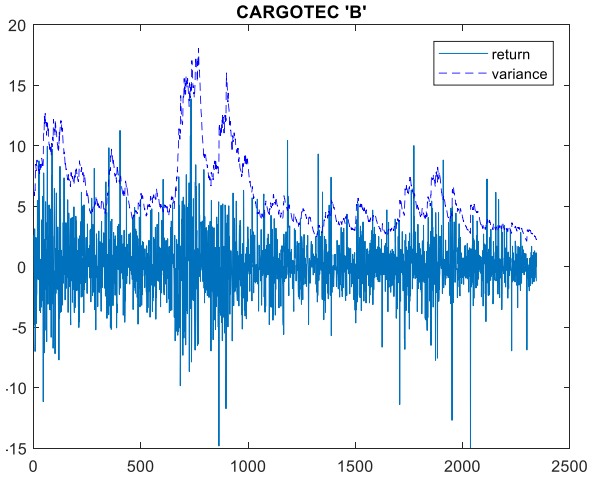

WARTSILA
return
variance

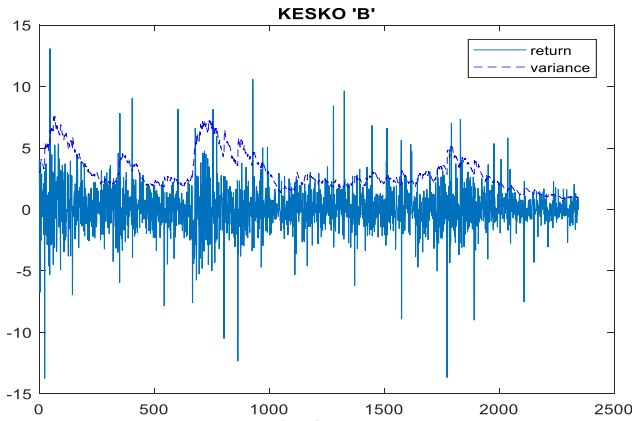

ELISA
return
variance

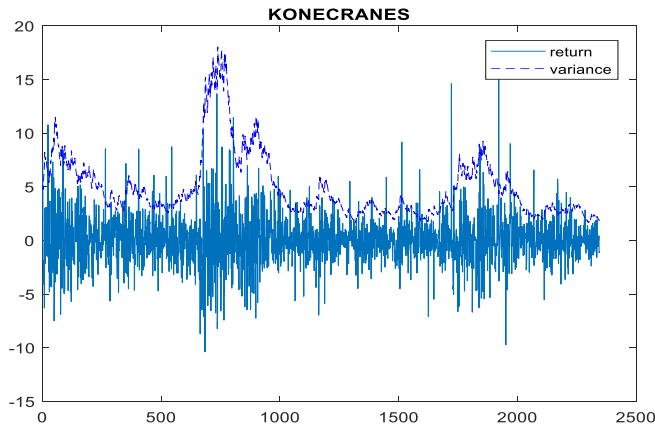

METSO
return
variance

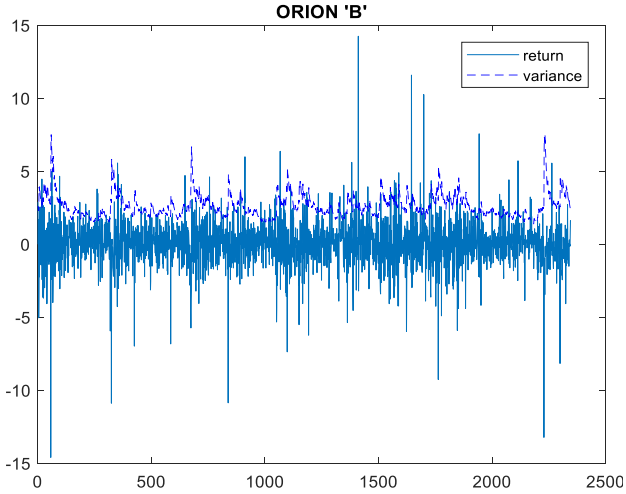

NOKIAN RENKAAT
return
variance

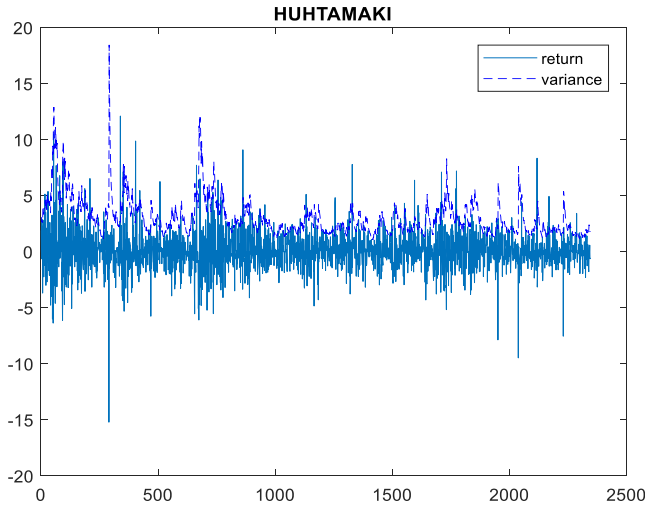

AMER SPORTS
return
variance

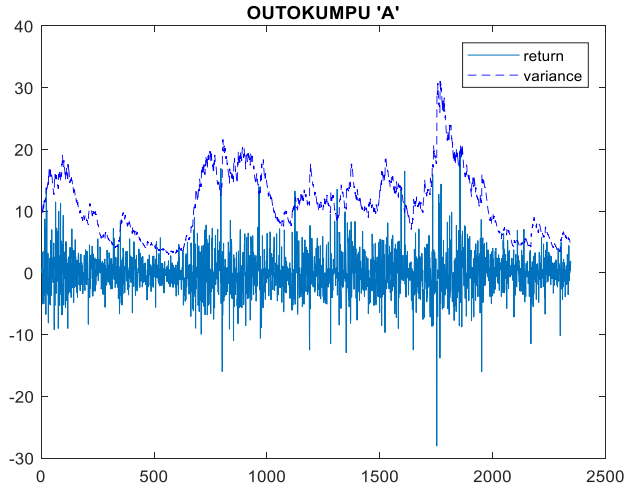

CARGOTEC 'B'
return
variance

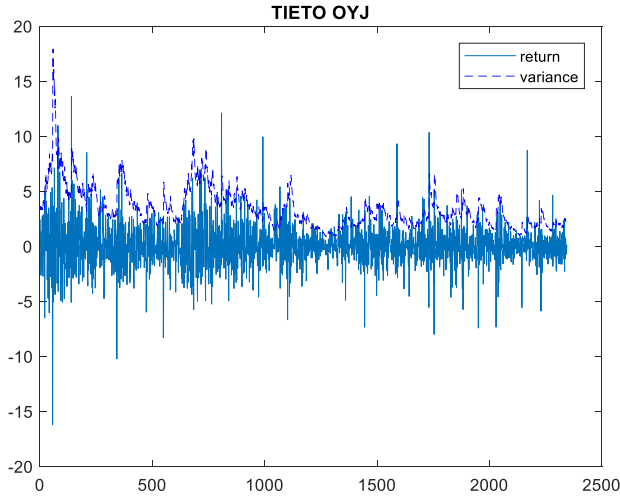

KESKO 'B'
return
variance

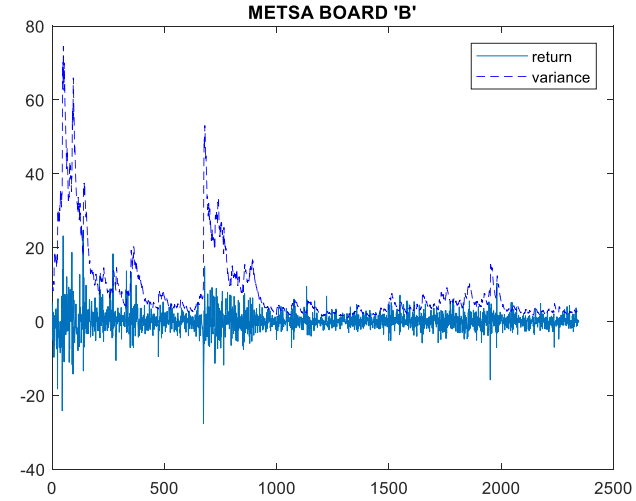

KONECRANES
return
variance

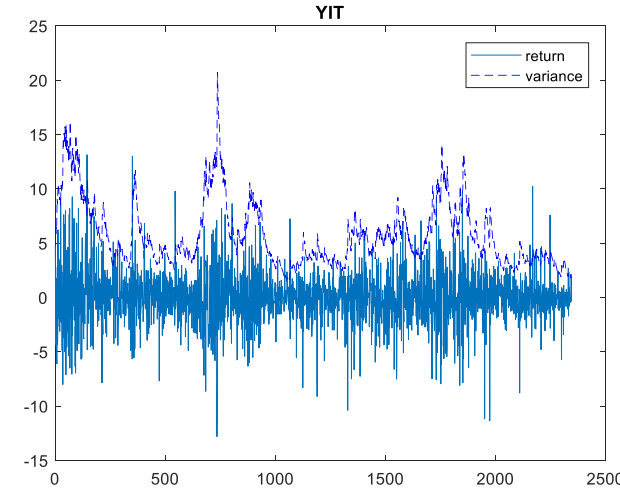

ORION 'B'
return
variance

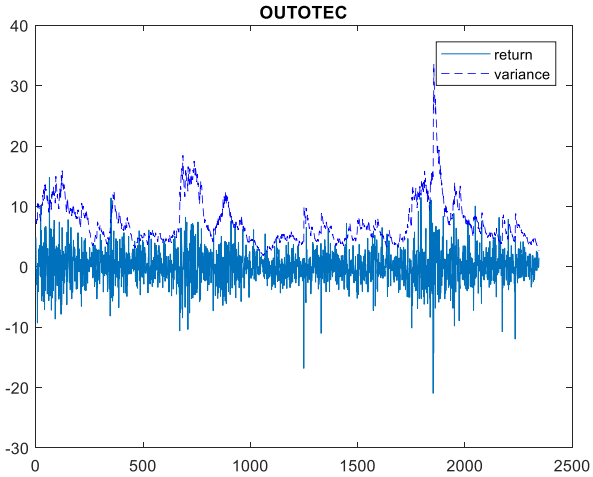

HUHTAMAKI
return
variance

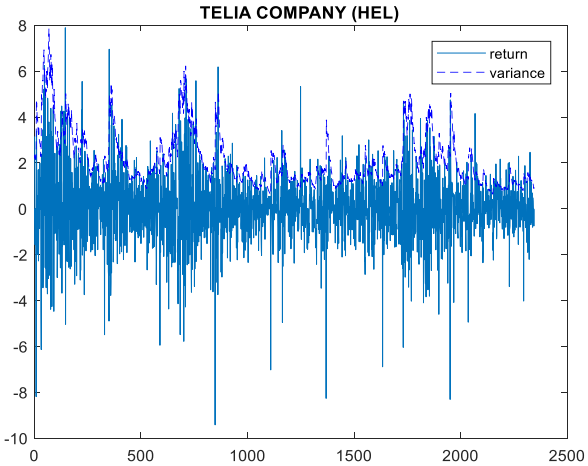

OUTOKUMPU 'A'
return
variance

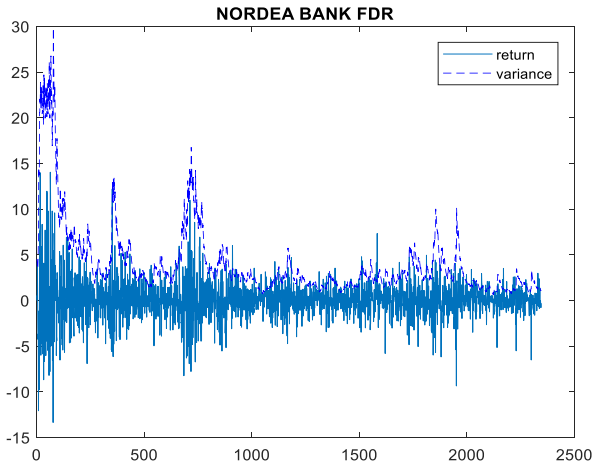

TIETO OYJ
return
variance


METSA BOARD 'B'
return
variance


YIT
return
variance



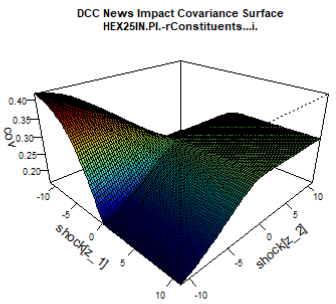


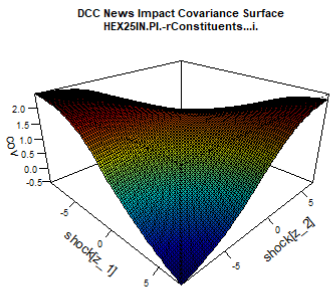


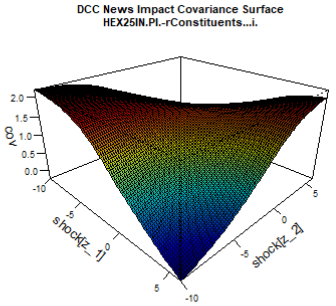
APPENDIX II: News Impact Surfaces

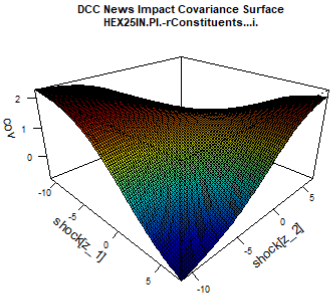
Here is news impact curve of 24 series (each plot contains 4 series). Shock[z_1] represents market shock and shock[z_i] represents corresponding firm shock. In particular. we are interested in asymmetric response of covariance given positive and negative shocks.

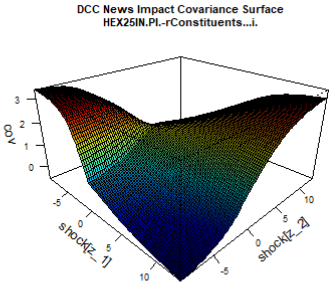
As can be seen. negative market shocks increase covariance for all series. In addition. positive firm shocks increase covariance for all series.

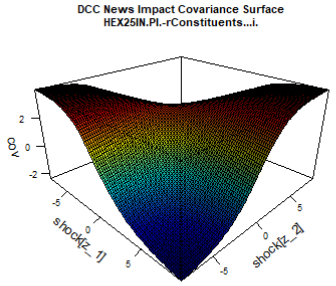


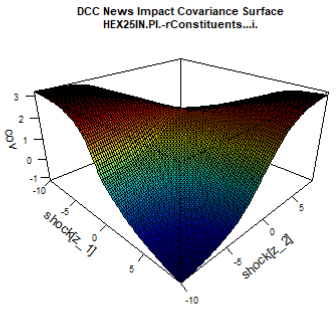


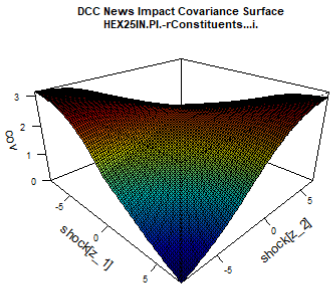






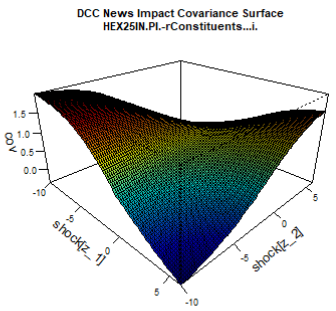


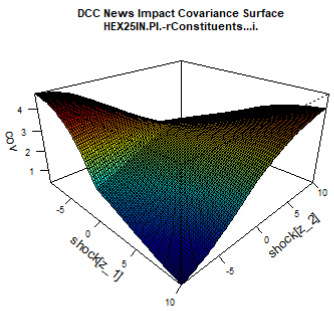


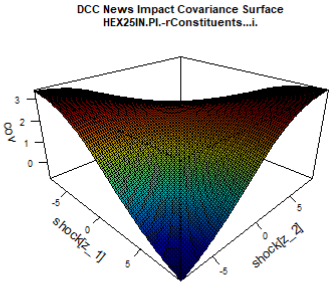


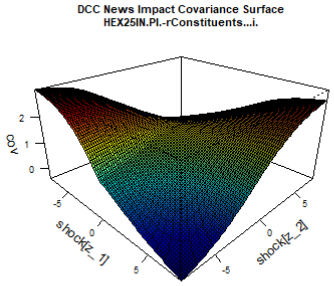
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
0.40
0.35
0.30
0.25
0.20
-10
-5
0
5
10
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
2.0
1.5
1.0
0.5
0.0
-0.5
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
2.0
1.5
1.0
0.5
0.0
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
2
1
0

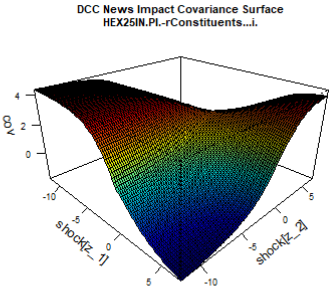
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
3
2
1
0
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
2
0
-2
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
3
2
1
0
-1
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
3
2
1
0

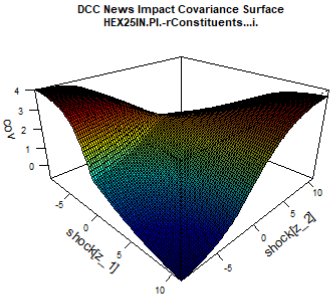


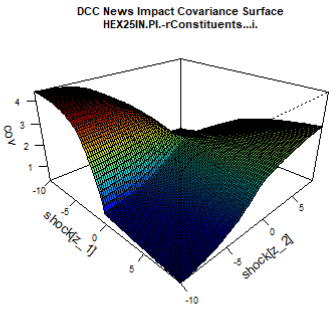


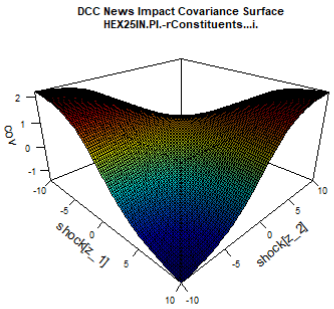






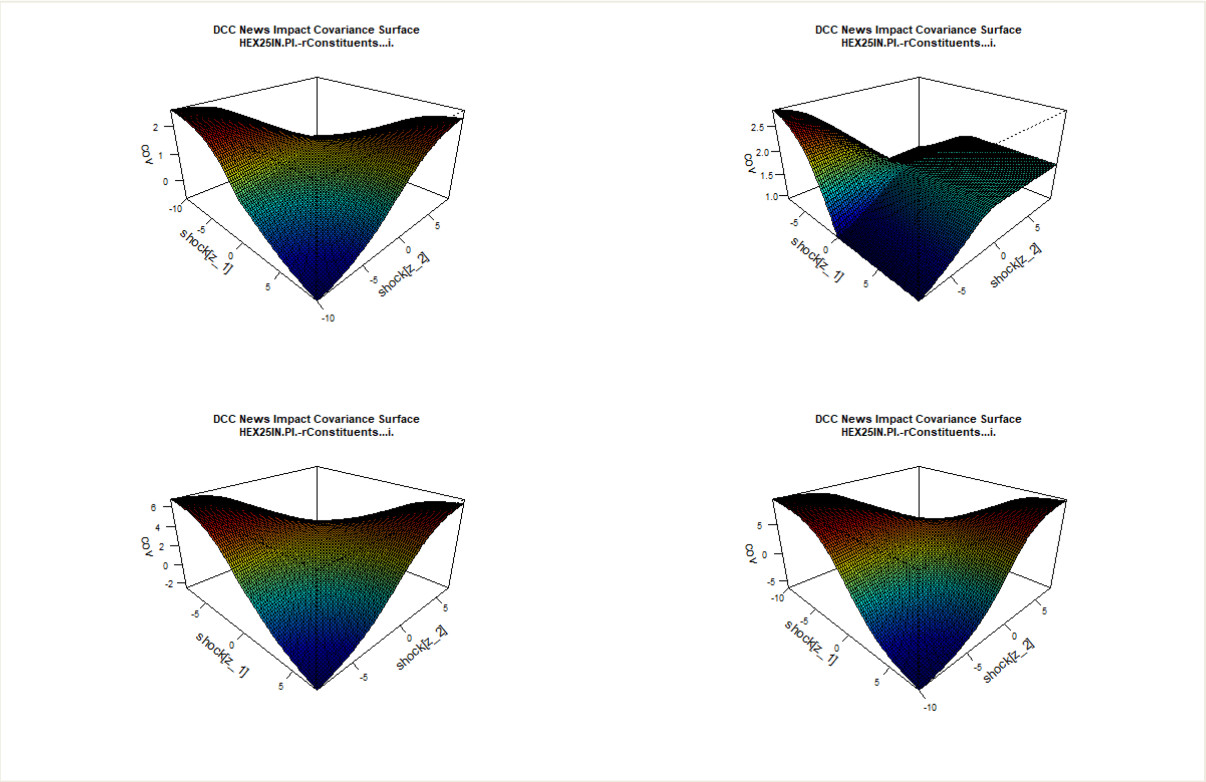


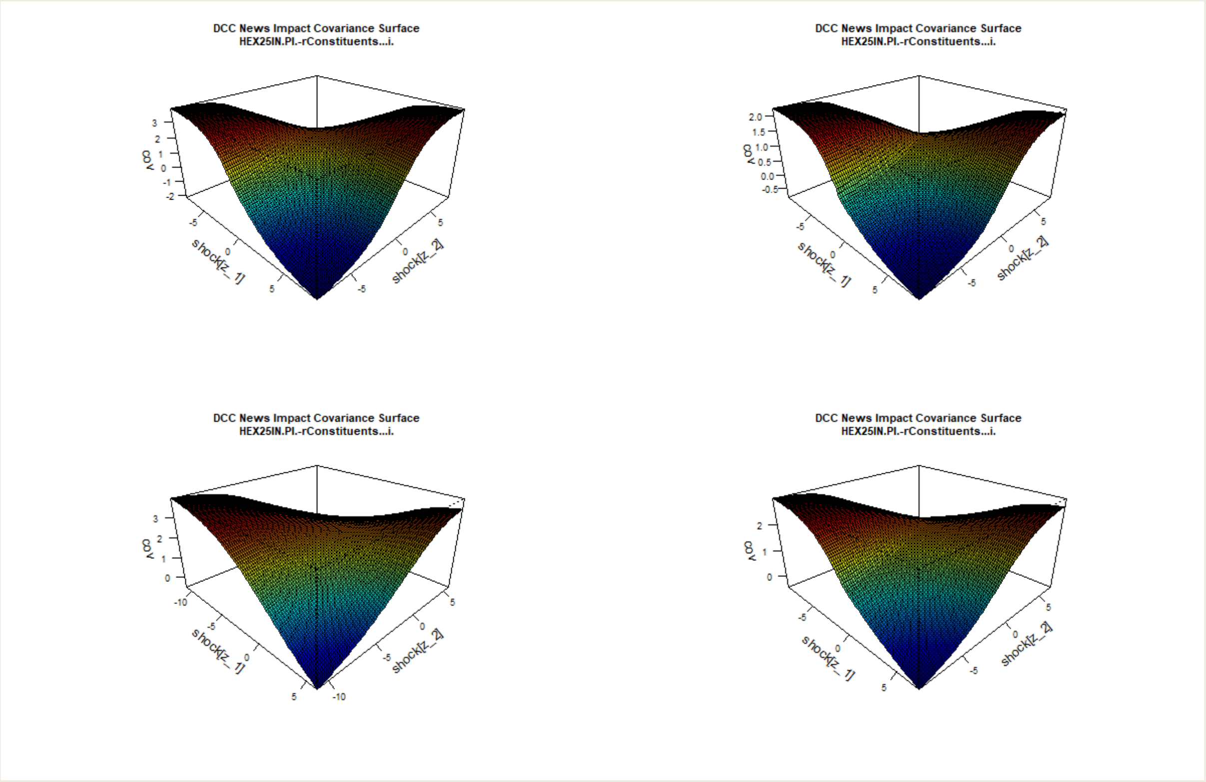




DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]

DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]


DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]


DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]
DCC News Impact Covariance Surface
HEX25IN.PI.-rConstituents...i.
cov
shock[z_1]
shock[z_2]

APPENDIX III: Conditional Covariance statistics

	Min	Max	Mean	Std. Dev.	Expected Risk Premium (%). daily	*Annual RP (%)
NOKIA	0.6068	7.6752	2.1071	1.2146	0.0208	5.4013
SAMPO	0.2540	7.8572	1.5043	1.2532	0.0148	3.8562
KONE	0.1768	6.7287	1.5421	1.1107	0.0152	3.9531
FORTUM	0.2731	6.0612	1.2586	0.9085	0.0124	3.2264
NESTE	0.2259	8.8597	1.6655	1.2234	0.0164	4.2694
UPM-KYMMENE	0.4743	10.1743	2.1167	1.4136	0.0209	5.4260
WARTSILA	0.2160	9.6083	1.9551	1.4388	0.0193	5.0119
STORA ENSO	0.4445	9.4738	2.2392	1.5893	0.0221	5.7401
ELISA	0.2333	3.6057	0.9804	0.6048	0.0097	2.5131
METSO	0.3138	12.7098	2.3037	1.8628	0.0227	5.9056
NOKIAN RENKAAT	0.2465	10.6477	2.0360	1.6747	0.0201	5.2191
AMER SPORTS	0.2990	9.2814	1.5804	1.2648	0.0156	4.0513
CARGOTEC	0.2115	9.1569	2.2075	1.5408	0.0218	5.6587
KESKO	0.2157	5.3907	1.2438	0.8242	0.0123	3.1885
KONECRANES	0.3915	9.8386	2.0423	1.5589	0.0201	5.2354
ORION	-0.0907	4.8856	1.0272	0.6040	0.0101	2.6332
HUHTAMAKI	0.2213	7.5996	1.3242	0.9877	0.0131	3.3946
OUTOKUMPU	0.3283	9.1401	2.5709	1.6841	0.0253	6.5905
TIETO OYJ	0.2885	6.9456	1.4005	0.9796	0.0138	3.5901
METSA BOARD	0.0474	14.4788	2.2444	2.2297	0.0221	5.7535
YIT	-0.0270	9.0841	2.0882	1.5127	0.0206	5.3531
OUTOTEC	0.4325	10.2518	2.3222	1.7158	0.0229	5.9529
TELIA COMPANY	0.0742	6.1431	1.2683	0.9747	0.0125	3.2513
NORDEA BANK FDR	0.2276	10.6537	2.0007	1.8687	0.0197	5.1287
Average	0.2535	8.5938	1.7929	1.3350	0.0177	4.5960

* Assuming 260 trading days correspond to a year