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Idiosyncratic volatility around information release date Evidence from the Helsinki Stock Exchange

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Abstract

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Several papers document idiosyncratic volatility is time-varying and many attempts have been made to reveal whether idiosyncratic risk is priced. This research studies behavior of idiosyncratic volatility around information release dates and also its relation with return after public announcement. The results indicate that when a company discloses specific information to the market, firm's specific volatility level shifts and short-horizon event-induced volatility vary significantly however, the category to which the announcement belongs is not important in magnitude of change. This event-induced volatility is not small in size and should not be downplayed in event studies. Moreover, this study shows stocks with higher contemporaneous realized idiosyncratic volatility earn lower return after public announcement consistent with "divergence of opinion hypothesis". While no significant relation is found between EGARCH estimated idiosyncratic volatility and return and also between one-month lagged idiosyncratic volatility and return presumably due to significant jump around public announcement both may provide some signals regarding future idiosyncratic volatility through their correlations with contemporaneous realized idiosyncratic volatility. Finally, the study show that positive relation between return and idiosyncratic volatility based on under-diversification is inadequate to explain all different scenarios and this negative relation after public announcement may provide a useful trading rule.

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IVOL: Idiosyncratic volatility

RIVOL: Contemporaneous (one month-realized) idiosyncratic volatility

LIVOL: One-month lagged idiosyncratic volatility

EIVOL: EGARCH estimated idiosyncratic volatility

1. Introduction

1.1 Statement of main problem and motivation

Recently the idiosyncratic volatility and issues thereof have become more interesting in financial studies. Although the capital asset pricing model (CAPM) suggests that all investors hold the market portfolio in equilibrium and only systematic risk is priced, investors in reality may not hold perfectly diversified portfolio, hence, they are engaged in idiosyncratic risk. In addition, Malkiel and Xu (1997) intimate that it is impractical to have all idiosyncratic risk removed from a portfolio and several authors[1] document an increase in amount of required stocks to diversify away idiosyncratic risk and as a result it is expected that under-diversification become more common and the role of idiosyncratic risk become more important. Moreover, some scholars such as Campbell et al. (2001) and Brandt et al. (2010) show that during different periods of time stocks have become more or less volatile. Other recent studies such as Fu (2009) and Bekaert et al. (2010) illustrate the idiosyncratic volatility is time-varying and owing to this variation in time many other issues in finance such as asset pricing models and event studies could be affected.

Furthermore, despite all attempts to determine whether or not idiosyncratic risk is priced, the results of recent papers regarding the magnitude and direction of the dependence seem to be contrasting and rather puzzling. Merton (1987) suggests that stocks with high idiosyncratic volatility have high expected returns, since when investors cannot fully diversify away firm-specific risk they demand a compensation for bearing idiosyncratic risk. On the contrary, Ang et al. (2006) corroborate that U.S. stocks with high lagged idiosyncratic volatility earn low future average returns. Similarly, they find identical results in other developed countries (Ang et al., 2009). However, Fu (2009) believes that Ang et al.'s findings are "a substantive puzzle" and argues that since idiosyncratic volatilities are time-varying, therefore, one-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of current month. His results suggest that returns are positively related to EGARCH estimated conditional idiosyncratic volatilities. Being similar to finding of Ang et al. (2009), Bali and Cakici (2009) represent a negative and

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1 . See for example Statman (1987), Campbell et al. (2001) and Kearney and Potì (2008)

significant relation between $IVOL_{daily}$[2] and the cross-section of expected returns. One year later, Huang et al. (2010) indicate that both findings of Bali and Cakici (2009) and Ang et al. (2006) can be explained by short term monthly return reversals. On the other hand, Sonmez (2010) proposes negative relation can happens when significant jumps in idiosyncratic volatility are included firm-month observations and Rachwalski and Wen (2013) document negative relation between idiosyncratic risk innovations and subsequent returns in temporary basis.

As a different point of view, idiosyncratic volatility is also important in event studies. Standard event study methods investigate the behavior of firms' stock prices around specific corporate events in which it is implicitly assumed equal event-induced variance for all securities in the sample. However, Bremer and Zhang (2007) show positive relationship between information flow and volatility and they document over event days, short-horizon event-induced abnormal returns and volatility vary significantly and Campbell et al. (2001) also believe that these methods could be potentially affected by the increase in the firm-level volatility. In addition, according to Aktas et al. (2009) in the presence of increasing idiosyncratic volatility as a key input to the standard event-study[3], the method significantly suffer from a loss of power in which the power is a decreasing function of the individual firm's specific risk.

This study concentrates on idiosyncratic volatility around information release dates, since it is estimated that idiosyncratic volatility is robust around information release dates and it is suitable time to study idiosyncratic volatility. Moreover, understanding the behavior of idiosyncratic volatility especially around public announcements which can influence the event study as a major tool in both finance and accounting is interesting and important simultaneously. Additionally, the risk-return relationship as a fundamental financial concept has been always attractive, specifically idiosyncratic risk about which there are huge debates and contrasting results. Besides that, the Helsinki Stock Exchange is the candidate to be studied as it is believed in relatively small and concentrated markets under-diversification is more prevalent and due to relatively narrow selection of securities, limited liquidity and more short sale

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2. Daily idiosyncratic volatility.

3. To calculate the test statistic.

constraints compared to major stock exchanges it is less possible to attain optimal portfolios; hence, the role of idiosyncratic volatility should be more visible and significant. Additionally, due to less market efficiency in emerging markets the portion of idiosyncratic in total volatility is lower than developed markets therefore; these markets are not ideal candidates for this specific study even if some of them are small and concentrated.

To be more exact, due to the fact that the content of announcement can provide some information regarding firm's specific risk and according to relationship between information flow and volatility, it is expected to witness significant shift at idiosyncratic volatility level around information release dates. Furthermore, intuitively the magnitude of these changes should be different in various categories[4] to which the announcement belongs. In addition, based on Miller's (1977) "divergence of opinion hypothesis" it is expected that after information release dates increases in risk imply higher degree of opinion divergence regarding the stock and that can lead to negative relation between return and idiosyncratic volatility.

1.2 Objectives of the study

The main objective of this research is to study behavior of idiosyncratic volatility around information release dates and also examine idiosyncratic risk and return relationship after public announcement and this is contribution of the study to the existing literature. Indeed, the objectives are as follows:
1) To investigate whether or not new information release affects idiosyncratic volatility?
2) To inspect whether or not the category to which information belongs affect the magnitude of change in idiosyncratic risk after the information release date?
3) To examine relation between idiosyncratic volatility and return after information release dates.

In order to achieve mentioned objectives, following techniques are employed:
1) Fama-French three factor model to measure idiosyncratic volatility.

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4. E.g. merger and acquisition verses change in management.

2) Repeated-Measures Designs and Paired t-test to explore the differences in idiosyncratic volatility levels at different points of time with respect to information release date.

3) One Way ANOVA to investigate the effect of information type on magnitude of change in idiosyncratic volatility after public announcement.

4) EGARCH method to estimate expected idiosyncratic volatility.

5) t test and GLS Regressions to find the relationship between idiosyncratic volatility and stock return.

1.3 Contribution

In this study, the idiosyncratic volatilities are measured over four distinct periods around public announcements (one month before, two weeks before, two weeks after and one month after announcement dates). The results indicate that information release affects idiosyncratic volatility level significantly, specifically in shorter-horizon. Information flow causes shifts in firm-level volatility and this event-induced volatility is not small in size and should not be ignored in event studies. This is consistent with a relationship between information flow and volatility[5]. Furthermore, this study documents partial evidence for the existence of information leakage, rumors and insiders dealing before public announcement and on the other hand, findings suggest no significant change in idiosyncratic volatility after two weeks of information release. Analyzing the magnitude of change based on three event categories namely interim report, management change and merger and acquisition reveals that the category to which the announcement belongs is not important in magnitude of change in idiosyncratic volatility. However, the content of announcements is substantial to change the level of idiosyncratic volatility and it is in line with previous papers[6] that attribute many extreme changes in idiosyncratic volatility to these three types of categories.

Additionally, the current study indicates stocks with higher contemporaneous realized idiosyncratic volatility earn lower return after public announcement. This is

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5. See for example Bremer and Zhang (2007) and Harrington and Shrider (2007).

6. See for example Sonmez (2010).

consistent with "divergence of opinion hypothesis"[7] and as increases in firm specific volatility after announcement days imply higher degree of opinion divergence regarding the stock, the negative relation in the study could be justified. Since divergence of opinion does not last for a long time it is possible to expect this relation as a temporary relationship. Moreover, there are other papers which suggest significant jumps in idiosyncratic volatility can derive negative relation between idiosyncratic volatility and return [8] and document negative relation between idiosyncratic risk innovations and returns although this relation only lasts a few months[9]. In this research, no significant relation is found between expected idiosyncratic volatility (through EGARCH) and return and also between one-month lagged realized idiosyncratic and return presumably due to significant jump in idiosyncratic volatility around information release dates. However, both of them may provide some signals regarding future idiosyncratic volatility through their correlations with contemporaneous realized idiosyncratic volatility. In addition, this study suggests that positive relation between return and idiosyncratic volatility based on under-diversification is inadequate to explain all different scenarios. Finally, this negative relation after information release date may provide a useful trading rule for both Finnish and international investors to decide on short holding period or long holding period and also portfolio managers should be aware that stock portfolios sorted by idiosyncratic volatility may yield negative or very low return if extreme increase in idiosyncratic volatility occur in significant portion of portfolio, and hence they should continuously monitor and reassess the condition.

1.4 Structure of the study

The rest of the study proceeds as follows. In section 2, a review on existing literature regarding idiosyncratic volatility with respect to given objectives are provided. In Section 3, hypotheses are developed and presented. Section 4, introduces the methodologies which are employed to test hypotheses and section 5 provides the description of the utilized data in order to conduct required tests. Section 6, presents the empirical results and analysis and finally, section 7 is conclusion of the study.

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7. See Miller's (1977).

8. See Sonmez (2010).

9. Rachwalski and Wen (2013)

2. Literature review

In this section, relevant literatures regarding idiosyncratic risk mainly with respect to research objectives are presented. Although concepts of volatility and risk are different, in the literature idiosyncratic risk and idiosyncratic volatility are usually treated as virtual synonyms. As a matter of fact, idiosyncratic volatility could be a useful proxy for idiosyncratic risk. Definition and measurement of idiosyncratic volatility is various among authors. While Malkiel and Xu (1997) use differences of stock return's variance and variance of the S&P 500 as idiosyncratic volatility, some other researchers such as Campbell et al. (2001) and Brandt et al. (2010) define idiosyncratic volatility as individual stock return minus industry return. In numerous papers the (standard deviation of) residual of asset pricing models is utilized as idiosyncratic volatility. Some of papers employed CAMP residual however; majority of them used Fama-French three factor model to calculate idiosyncratic volatility.

2.1 Idiosyncratic risk

The capital asset pricing model (CAPM) of William Sharpe (1964) and John Lintner (1965a) is built on portfolio theory in which it is assumed investors hold a portfolio of stocks to diversify firm's specific risk and suggests that all investors hold the market portfolio in equilibrium. CAPM implies a positive relationship between expected return of the asset and their market betas and other factors should not explain expected returns and hence only systematic risk is priced.

On the other hand, Roll (1977) claims since it is not possible to have comprehensive definition of market portfolio it is also rather impossible to test CAPM empirically. However later, several papers prove that market beta alone is not sufficient and as it is documented size (Banz, 1981), price to earnings ratio (Basu, 1983), book-to-market (Rosenberg et al., 1985) and leverage (Bhandari, 1988) are some other factors to explain the cross-sectional returns. Consequently, the fact that CAPM cannot capture all the priced sources of risks result in developing other models such as Merton's (1973) Intertemporal Capital Asset Pricing Model. In 1993 Fama-French introduced their three factors model and later Carhart (1997) proposed momentum

factor, however, up to now there is no comprehensive model to explain stocks' expected return with respect to all sources of risks and factors.

From another point of view, Malkiel and Xu (1997) argue it is impractical to have all idiosyncratic risk removed from a portfolio. Bloomfield et al (1977) report based on their sample from 1965 to 1970, a diversified portfolio could be achieved with fewer stocks than 20. Later, Statman (1987) suggests at least 30 and 40 stocks for a borrowing and a lending investor respectively while Campbell et al. (2001) in their more recent study maintain for a relatively complete portfolio diversification, almost 50 stocks are required and they state "the number of stocks needed to obtain any given amount of portfolio diversification has increased" (Campbell et al., 2001 p.40). Similarly, findings of a research by Kearney and Potì (2008) support an increase in amount required stocks to diversify away idiosyncratic risk in Euro area.

Furthermore, in reality due to various factors such as age, income-level, education-level, being less-sophisticated investor, over-confidence, trend-following behavior and local bias which are suggested by Goetzmann and Kumar (2004), investors may not hold perfectly diversified portfolios. Merton (1987) argues due to transaction costs and lack of short-sell for small companies it is difficult to form a well-diversified portfolio. In addition, according to a sample includes more than 62,000 household investors over the period of 1991 to 1996, Goetzmann and Kumar (2004) indicate only less than 10% of the investor portfolios comprise more than 10 stocks, over 50% of the investor portfolios contain no more than three stocks and over a quarter of investors hold only one stock. In brief, according to all preceding mentioned points it seems that both sources of risk, systematic and unsystematic may matter to investors.

2.2 Idiosyncratic risk matters

In 1997, Malkiel and Xu find contradictory result to traditional capital asset pricing model and they show that idiosyncratic volatility (is highly correlated with firm size and) is related to stock returns and explains a considerable part of average stock returns' variation. Later, Malkiel and Xu (2002) claim that when due to exogenous reasons some investors does not hold the market portfolio, it is not possible for other

investors to hold the market portfolio as well. Hence, idiosyncratic volatility affects asset returns.

In the same way, Goyal and Santa-Clara (2003) intended to provide more evidence regarding a conflicting and confusing issue in asset pricing and to know whether or not idiosyncratic volatility is a priced factor. In their provocative paper, they claim that empirical literatures that have tried to establish risk-reward tradeoff for the aggregate stock market have been inconclusive. In addition to market risk in their study, they take average stock variance into consideration, as they believe this is mainly driven by idiosyncratic risk. As a matter of fact, their study is to explore the time-series relation between average stock risk and the stock market return. Their results suggest while average stock variances have predictive power for market return and the relationship is positive, there is not such a predictive power for market variance.

Afterwards, Wei and Zhang (2005) re-examined the relationship between average returns and average volatilities suggested by Goyal and Santa-Clara (2003) in extended sample periods and they argue this positive relation is driven by the data in the 1990s and in their sample from 1963.08 to 2002.12 after excluding the 1990s' data the relationship disappears. In addition, Bali, et al. (2005) explain that Goyal and Santa-Clara's (2003) findings is due to small stocks traded on the NASDAQ and partially by a liquidity premium.

Nevertheless, Drew et al. (2004) show that idiosyncratic volatility is also priced at Shanghai Stock Exchange and multifactor models are more powerful than CAPM to describe average returns. In a recent paper, Angelidis and Tessaromatis (2009) use a regime switching model in U.S. market and reveal while the there is no significant relationship between risk and return within the high variance state, it is statistically significant only during low variance regime. Huimin et al. (2010) confirm Goyal and Santa-Clara (2003) finding that idiosyncratic risk matters (especially for socially responsible investments) and using the Markov Switching Model they find relatively the same results with Angelidis and Tessaromatis (2009) and figure out that a in low

and medium volatility regime there is positive relation between idiosyncratic risk and SRI[10] returns, however not for high volatility states.

2.3 Time variation in idiosyncratic risk

There are evidences that stocks have become more or less volatile over time in different periods. Besides that, time-varying behavior of idiosyncratic risk is also documented in the recent literature. Campbell et al. (2001) characterize behavior of stock market in three different levels namely, market level, industry level and firm level over the period from 1962 to 1997. Using a disaggregated approach they figure out positive deterministic trend in firm-level idiosyncratic volatility however, no analogous attitude for industry and market volatility. Their findings suggest a decline in correlations between individual stock returns over previous decades and they claim that the upward trend in idiosyncratic volatility is not just because of quantitative growth in publicly traded firms or owing to variations in the serial correlation of daily data. Hence, due to more exposure to idiosyncratic risk for investors who do not hold a well-diversified portfolio the implications of the findings are more significant in their opinion.

Accordingly, Campbell et al. (2001) findings have attracted many other researchers to study time-trend of idiosyncratic volatility. Using Fama-French factor model, Malkiel and Xu (2003) show over the 1980s and 1990s, while market volatility has not shifted substantially, firm's specific volatility has trended up. Fink et al. (2005) follow disaggregated approach and document the increase idiosyncratic volatility however, once they control for young companies the trend disappears and even it becomes negative by controlling for firm maturity. Based on a sample from 1955 to 2000, Comin and Philippon (2005) also show a growth in firm-level volatility and a negative relationship with aggregate volatility. Gaspar and Massa (2006) use Fama-French factor model to measure idiosyncratic volatility over 1962 to 2001 and to examine relationship between competitive environment and firm volatility. They support upward trend in idiosyncratic volatility. Similarly, an increasing trend in firm's level volatility is found by others such as Wei and Zhang (2006), Brown and Kapadia (2007), Cao et al. (2007) and Irvine and Pontiff (2009).

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10. Socially responsible investments

Above mentioned papers mainly focused on the U.S. market however, Frazzini and Marsh (2002) study U.K. market and document there is no such an upward trend in firm level volatility (Comin and Philippon, 2005). On the contrary in France, Thesmar and Thoenig (2004) report an increase in firm level volatility specifically for listed companies. Kearney and Potì (2008) attempted to understand whether or not Campbell et al. (2001) finding is valid for European countries. Following identical methodology for a sample of companies in Euro area from 1974 to 2004 they find an increase in idiosyncratic volatility, although as opposed to them an upward trend in market risk is witnessed and they show Correlations among individual stocks have not declined. Angelidis (2010) in his study on idiosyncratic risk in emerging markets indicate that increase in idiosyncratic risk is not a global phenomenon and suggests due to less market efficiency in emerging markets the portion of idiosyncratic in total volatility is lower than developed markets and for most of the emerging markets neither total volatility's ingredient nor the average correlation between stock returns show a trend.

However, two of the most recent studies on idiosyncratic risk trend in U.S. refute Campbell et al. (2001) increasing trend. Following identical methods, Brandt et al. (2010) document in later years unsystematic risk has declined substantially, offsetting upward trend in previous studies (during the 1962–1997) and dropped back to pre-1990s and they indicate that "the increase in idiosyncratic volatility through the 1990s was not a time trend but, rather, an episodic phenomenon" (p.863) and it is more apparent in low-priced stocks which are held relatively more by retail investors. Bekaert et al. (2010) argue that Campbell et al. (2001) results are due to temporary increase in idiosyncratic volatility in the 1990s and their findings are actually sensitive to various methodologies and sample periods. Bekaert et al. (2010) conduct a comparative study to examine the aggregated unsystematic volatility on international data in 23 developed stock markets from 1980 to 2008. Their findings reveal there is no upward trend when the sample period is extended to 2008. Similarly, they found no significant evidences for upward trend in idiosyncratic volatility in other developed countries and even they found downward trend for nine countries (including Finland). From a different point of view, Vozlyublennaia (2011) investigates idiosyncratic volatilities' fluctuation by studying individual securities.

Their results imply approximately half of the securities have long periods of increasing idiosyncratic risk or periods of a long decrease in idiosyncratic risk however, the proportions fluctuate over time and consequently, individual securities affect the market average. They indicate average idiosyncratic risk may have different behavior from idiosyncratic risk of an individual security and hence, conclusions based on average may not be applicable to a given portfolio due to various dynamics across securities.

Beside the focus on the trend, there are endeavors to reveal what factors are related to these trends and propose explanations for this phenomenon. Competition enhancement that can result in cash flow variability as a factor which can push idiosyncratic volatility upwards is mentioned by Gaspar and Massa (2005), Irvine and Pontiff (2009) and also Comin and Philippon (2005) who suggest that this increase in competition is associated with large research and development expenditure and higher leverage. Moreover, Chun et al. (2008) support the effect of this intensive investment and also state that financial systems development can raise firm' specific variability compared to total market variability. Some other authors such as Malkiel and Xu (2003) and Bennett et al. (2003) indicate positive relation between growth of trades by institutional ownership and increase in idiosyncratic volatility. Fink et al. (2005) refer to substantial fall in corporation's age from 40 years old in the early 1960s to below 5 years when they intent to IPO and their tendency to be a publicly traded company at an earlier stage in their life cycle push up idiosyncratic volatility however, Brown and Kapadia (2007) suggest these increase is caused by more risky companies being listed on stock exchange. Wei and Zhang (2006) argue since earnings are less subject to manipulation than dividends they are more informative for future profitability and show that when ROE of the firm became more volatile an upward trend in idiosyncratic volatility occurs and this is more apparent for newly listed firms than others.

Moreover, Cao et al. (2007) claim that they have found an explanation beyond other alternatives which is robust for different measures and proxies and that is available growth opportunities to managers of the firm and this factor is positively related to upward trend in firm-specific volatility. Using G7 countries' data Guo and Savakis (2008) suggest change in investment opportunities explain the trend in idiosyncratic

volatility and Bekaert et al. (2010) argue that growth opportunities, total (U.S.) market volatility and variance premium are three explanatory factors for variation in idiosyncratic volatility. Additionally, Brandt et al. (2010) attribute the temporary upwards trend to speculative behavior and they believe that it is evidenced by market bubbles while Rajgopal and Venkatachalam (2011) figure out that earning quality have negative relationship with idiosyncratic return volatility over 1962–2001. Bekaert et al. (2010) categorize determinants into three paramount parts. First one is regarding "the changing composition of stock market indices" (p.3), second category belongs to "firm-specific characteristics that ultimately determine idiosyncratic cash flow variability" (p.3) and the third are the explanations which are "behavioral in nature" (p.3). Indeed, majority of previously mentioned factors belongs to the second category.

Despite all attempts, it is not possible to have certain conclusion regarding what factors stimulate idiosyncratic volatility and how to predict next episodic trend. However, either upward or downward trend through the years and historical periods, intuitively, idiosyncratic volatility should shift over time due to the fact that it mirrors information regarding the firm which are not essentially persistent through the time such as periodical earnings reports. Bekaert et al. (2010) maintain linear models are poor to describe the trend in firm's specific volatility. Vozlyublennaia (2011) suggest firm's level idiosyncratic volatilities are able to forecast likelihood of fluctuations in the future. Econometric models such as GARCH have been developed to describe the volatility property of asset returns and Fu (2009) suggests the idiosyncratic volatilities possess time-series behavior and shows it is not persistent through the time and hence he employ EGARCH specification to predict future volatilities.

2.4 Idiosyncratic volatility and expected return

In this part, first the most influential papers that suggest and justify either positive or negative relation between idiosyncratic risk and expected return are discussed. Then a brief review of relevant theories is provided. Finally, other empirical findings of various papers are presented.

2.4.1 The most influential papers

Understanding of the most influential papers is essential to sort out the idiosyncratic volatility and return issue. These papers are: Merton (1987), Campbell et al. (2001), Goyal and Santa-Clara (2003), Ang et al. (2006) and Fu (2009). Modern portfolio theory suggests in equilibrium, firm-specific risk should not be priced in the cross-section of expected returns due to the fact that it could be eliminated through diversification. However, Merton (1987) argues "financial models based on frictionless markets and complete information are often inadequate to capture the complexity of rationality in action" (p.484) and develops "investor recognition" hypothesis (IRH) in which trading behavior of investors is affected by incomplete information dissemination. More precisely, although all investors have homogeneous expectations not all of them have information about all assets therefore; they tend to overinvest in securities that have more information about them. Hence, they hold under-diversified portfolio and expect higher return to compensate for imperfect diversification. In other words, investors demand for higher idiosyncratic risk premium due to less diversification and, thus, in equilibrium securities returns should be positively related to their idiosyncratic risk in addition to the systematic risk premium.

Although Campbell et al. (2001) do not study relationship between idiosyncratic volatility and cross-sectional returns their results have triggered numerous paper on the role of idiosyncratic volatility in asset pricing and stock return. Their findings imply idiosyncratic risk has the paramount portion in total risk and firm-level volatility provides predictive power for changes in market volatility. As they have indicated, the number of stocks required to achieve well-diversified portfolio has increased over time and this fact presumably increases individuals who hold under-diversified portfolios. From a different point of view, Goyal and Santa-Clara (2003) study Intertemporal relationship between total variance[11] and market returns. They report a positive relationship between average idiosyncratic volatility and one-month-ahead excess market returns and this finding remains intact after controlling for business cycle fluctuations and liquidity variables.

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11. As a proxy of idiosyncratic risk.

Ang et al. (2006) present their so called "the idiosyncratic risk puzzle" by documenting a negative cross-sectional risk-return relation. In their study from 1963 to 2000 on US Market, standard deviation of the FF-3 residuals is employed as the proxy of idiosyncratic risk. They create value-weighted portfolios according to idiosyncratic volatility of the previous month and show quintile portfolio that have highest idiosyncratic risk generate negative return. In addition, they report a zero-cost portfolio which is long in the fifth quintile and short in first yields negative price of risk. As a result, they conclude stocks with lower lagged idiosyncratic risk earn higher expected returns and claim the conclusion remains the same after controlling for aggregate volatility risk, size, book-to-market, liquidity, momentum, coskewness and dispersion in analysts' forecasts. The result contradict Merton's (1987) investor recognition hypothesis.

After Ang et al. (2006) published their result there have been many attempts to solve the puzzle. Fu (2009) challenges the negative relationship and show idiosyncratic volatilities have time-varying property and argue since risk-return relation is contemporaneous, one month lagged idiosyncratic volatility is not a good proxy to predict expected return. Hence, their finding is not applicable to explain relationship between idiosyncratic risk and expected return. Additionally, in portfolio-based approach idiosyncratic risk could be faded away and idiosyncratic risk of a portfolio would be lower than average of its component, thus he employs regressions for individual stocks. Using exponential generalized autoregressive conditional heteroskedasticity (EGARCH) in order to capture the time varying property of idiosyncratic volatility, Fu (2009) conducts monthly cross-sectional regressions for individual stocks and figures out a strong positive relation between (estimated) idiosyncratic volatility and expected returns in US market. Finally, Fu (2009) suggests that Ang et al. (2006) findings could be explained by return reversal of small and high idiosyncratic risk stocks.

2.4.2 Theoretical review

In addition to, Merton (1987), Malkiel and Xu (2002) assume under-diversification and predict idiosyncratic risk is positively related to cross-sectional expected returns due to the fact that if investors fail to hold the market portfolio they demand a compensation for bearing idiosyncratic risk. This under-diversification assumption

was previously mentioned by Levy (1978) who implicitly has suggested a role for idiosyncratic risk in asset pricing. Moreover, a behavioral model by Barberis and Huang (2001) based on loss aversion[12] and narrow framing[13] also suggests a positive relation between idiosyncratic risk and stock returns. From another perspective, Eiling (2013) refers to importance of human capital as non-tradable assets in asset pricing and argue since human capital is not homogeneous among individuals, excluding that from asset pricing model cause idiosyncratic risk and all this account for idiosyncratic risk premium.

On the other hand, Miller's (1977) "divergence of opinion hypothesis" can justify negative relationship between returns and idiosyncratic risk. He challenges the key assumption of homogeneous expectation in standard capital asset model and argues under short sale constraints dispersion of opinion leads to stock price overvaluation. Since increases in risk imply higher degree of opinion divergence regarding the stock, there should be a negative relation between firm's risk and risk-adjusted returns. In addition, based on risk averse investors concept, Chen (2002) suggests investors lower present consumption when uncertainty rises as a preventative measure and this idea also can explain why Idiosyncratic volatility could be negatively priced.

2.4.3 Empirical evidence

Two of the earliest studies on cross-sectional relationship between lagged idiosyncratic volatility (CAPM residuals) and return are by Lintner (1965b) and Lehmann (1990) in which both report positive relation. Later, Malkiel and Xu (2004) employ total variance as a proxy for idiosyncratic risk and show positive relationship and suggest this relation is more powerful when firm size and book-to-market equity are as control variables in the cross-section of expected returns. In 2006, Ang et al. present their controversial result and document U.S. stocks with high lagged idiosyncratic volatility earn low future average returns, and these assets are indeed mispriced by the Fama-French model. Their result triggered numerous subsequent studies, Bali and Cakici (2009) also use Fama-French model residuals and lagged

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12. To be more sensitive to avoid losses than to accumulate gains.

13. The attitude to concentrate particular stocks.

volatility however, they find negative and significant relation between $IVOL^{daily}$ and the cross-section of expected returns, whereas the cross-sectional relation between $IVOL^{monthly}$ and expected stock returns is flat. Ang et al. (2009) also show that as the formation periods increases, the magnitude of the coefficients on idiosyncratic volatility decrease.

Furthermore, Bali and Cakici (2009) believe data frequency used to calculate idiosyncratic risk, weighting scheme adopted for generating average portfolio returns, breakpoints utilized to sort stocks into quintile (or deciles) portfolios and using a screen for size, price and liquidity, play a critical role in determining the presence and significance of a cross-sectional relation between idiosyncratic risk and expected returns. Bali and Cakici (2009) document after excluding the smallest, least-liquid, and lowest-priced stocks, there is no evidence for a significant link between idiosyncratic risk and the cross-section of expected returns. They believe that idiosyncratic volatility effect reported by Ang et al. (2006) disappears after a screen for size, price and liquidity, implying that it is small and illiquid stocks that are driving their results. However, Huang et al. (2010) indicate that both findings of Bali and Cakici (2009) and Ang et al. (2006) can be explained by short term monthly return reversals. They also believe that no robust and significant relation exists between idiosyncratic risk and expected returns once they control for return reversals. Sonmez (2010) suggests significant shifts in idiosyncratic volatility drive Ang et al's results. Additionally, Rachwalski and Wen (2013) argue assuming under-reaction, when idiosyncratic risk increases, stocks will earn low returns however, on temporary basis.

In contrast, Fu (2009) believes that Ang et al.'s finding is "a substantive puzzle". He argues that since idiosyncratic volatilities are time-varying, therefore the one-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of current month. His results suggest that returns are positively related to EGARCH estimated conditional idiosyncratic volatilities. Jiang et al. (2009) find inverse relationship between idiosyncratic return volatility and earning shocks and also future earnings. As earnings are paramount determinant of stock returns, it explains the inverse relation between IVOL and future stock returns. Controlling for future earning shocks, there is not a significant negative relationship between IVOL

and stock returns. Spiegel and Wang (2005) and Huang et al. (2010) also use Fama-French model residuals, employ EGARCH and confirm positive relation between expected idiosyncratic volatility and the return. On the other hand, Ang et al. (2009) expand their previous studies and find similar results. They claim their idiosyncratic volatility effect is not necessarily the same with Fu's EGARCH estimated volatility. However, in one of most recent papers Eiling (2013) utilize EGARCH based on CAPM residuals and suggest positive relation between idiosyncratic risk and return.

Considering other possible factors, Fu (2009) shows that conditional idiosyncratic volatilities are negatively related to size and book-to-market equity ratio, and are positively related to BETA and to liquidity variables. Small firms tend to have higher idiosyncratic volatilities than large firms; growth firms tend to have higher idiosyncratic volatilities than value firms; liquid firms tend to have higher idiosyncratic volatilities than illiquid firms. Similar to Fu (2009), Bali and Cakici (2009) indicate a strong negative correlation between firm`s market capitalization (size) and idiosyncratic volatility. They also represent that idiosyncratic volatility is driven by small stocks traded on NASDAQ, and it is in part due to a liquidity premium. Nevertheless, Jiang et al. (2009) argue that high idiosyncratic volatility and low future returns are both related to a lack of information disclosure among firms with poor earning prospects.

Moreover, Lee and Liu (2007) show that the relation between price informativeness and idiosyncratic return volatility is U-shaped[14]. Song (2009) believes that the puzzling negative correlation between idiosyncratic volatility and return is a manifestation of financial distress. Ang A. et al (2009) include PIN (private information), the percentage of zero returns[15], the number of analysts, and the proportion of institutional ownership, delay measure, and skewness as control variables. They found that the coefficients on the control variables are insignificantly different from zero. Angelidis and Tessaromatis (2009) indicate that the positive and significant relation between idiosyncratic risk and return in low variance regime is robust to the weighting scheme by which average idiosyncratic risk is calculated.

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14. Increasing then decreasing.

15. To measure transaction cost.

Majority of papers have studied U.S. Market however, there are some other authors who have investigated relationship between idiosyncratic risk and expected return in other territories. Ang et al. (2009) replicate their 2006's study on U.S. market for 23 developed countries and argue after controlling for world market, size, and value factors their low returns for high idiosyncratic volatility puzzle is valid around the globe. They indicate the finding is significant either for each G7 country or pooled sample of 23 markets. They also represent co-variation in relation between lagged idiosyncratic volatility and average returns in developed countries. This high degree of co-variation suggests that what is driving the very low returns to high idiosyncratic volatility stocks around the world cannot be easily diversified away. Brockman et al. (2009) also have tried to reveal relation between idiosyncratic risk and expected returns in international environment. Following Fu's (2009) EGARCH model for 44 countries from 1980 to 2007, they support positive and significant relation for 36 countries out of the 44 and also positive but no significant for eight countries (including Finland). They argue investors under diversification accounts for this idiosyncratic risk premium and also document this risk premium in countries with higher investor risk tolerance and lower investor wealth is more extensive.

Additionally, Angelidis and Tessaromatis (2008) examine relationship between average idiosyncratic volatility and future returns in UK stock market and argue idiosyncratic volatility is important only for asset pricing of small capitalization stocks and in small stocks it predicts small capitalization premium but not for either the market or the value premium. They also indicate that there is no relationship between idiosyncratic volatility and business cycle or liquidity variables. Guo and Savakis (2008) in their study on average idiosyncratic volatility in G7 countries investigate intertemporal relationship between idiosyncratic risk and future market return and show that idiosyncratic volatility explains the cross section of stock returns as well as book to-market factor. Miralles-Marcelo et al. (2012) study asset pricing with idiosyncratic risk in the Spanish context and argue idiosyncratic volatility has large portion of total volatility. They conduct their research both on individual and aggregated level and report a significant and positive relation between firm-specific volatility and future returns on individual stock setting and furthermore, when

innovations in aggregate idiosyncratic risk [16] and one period-lagged aggregate idiosyncratic risk are examined, the relations are negative.

Considering 24 emerging markets, Angelidis (2010) argues due to less market efficiency in emerging markets the portion of idiosyncratic in total volatility is lower than developed markets. Employing lagged idiosyncratic volatility to explain monthly (and quarterly) market return he suggests "Idiosyncratic risk forecasts market returns only in conjunction with stock market risk" (p.1075) and using pooled data for all markets in the study provide negative and significant coefficient of idiosyncratic risk. Moreover, Drew et al. (2004) study Shanghai Stock Exchange, employing both CAPM model and Fama and French three factor model and utilizing mimicking portfolio approach of Fama and French reveal compared to big firms with high idiosyncratic volatility, small firms with low idiosyncratic volatility can provide higher returns and for Chinese investors higher idiosyncratic volatility is associated with a lower risk premium. Bley and Saad (2012) consider frontier markets of (Persian) Gulf Cooperation Council to study, and support the idea that high-lagged realized idiosyncratic risk is associated with low returns specifically for individual stocks in Saudi Arabia and Qatar. They also argue that control factors of momentum, liquidity, and leverage does not affect the result. In addition, they support Fu (2009) and report contemporaneous positive relationship between estimated idiosyncratic volatility (by EGARCH) and stocks returns and they suggest that this finding is robust to return reversals and other control variables.

2.5 Idiosyncratic volatility and event study

Standard event study methods investigate the behavior of firms' stock prices around specific corporate events in which equal event-induced variance for all securities in the sample is implicitly assumed. According to Kothari and Warner (2007) over recent years, main statistical templates of event studies has not transformed and paramount focus still remained on "measuring the sample securities' mean and cumulative mean abnormal return around the time of an event" (p.3) and significant changes are due to use of higher frequency data rather than monthly, in addition to sophistication of techniques in abnormal returns estimation and their statistical

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16. In the Intertemporal CAPM.

significance evaluation. Event studies use total risk, in which a considerable part is idiosyncratic (Brown and Kapadia, 2007). Idiosyncratic volatility is important in event studies as a key input in order to determine the statistical significance of abnormal event-related returns. AS It is mentioned earlier, Campbell et al. (2001) documents tocks have become more volatile over time and they also argue event study methods could be potentially affected by the increase in the firm-level volatility moreover, Kothari and Warner (2007) maintain volatility as an event-sample firm characteristic can affect properties of event study. Aktas et al. (2009) investigate the result of an event study[17] and note comparing two periods (before and after 1999) statistical significance is lower after 1999, in spite of similar CAR levels and sample sizes. They suggest it is presumably attributable to increase in the idiosyncratic volatility level.

In addition, Bremer and Zhang (2007) show positive relationship between information flow and volatility. Sonmez (2010) find business events bring majority of changes in idiosyncratic volatility and it is normally associated with an announcement or an event increases uncertainty about a stock. If the event is associated with uncertainty event period return variability is presumably more than other times and hence, statistical significance is overstated when it is based on historical variability (Kothari and Warner, 2007). Furthermore, according to Aktas et al. (2009) in the presence of increasing idiosyncratic volatility the method significantly suffer from a loss of power in which the power is a decreasing function of the individual firm's specific risk. In addition to poor test power, if the event-study methods consider volatility constant during event days they will have more potential for Type I error (Bremer and Zhang, 2007). This high failure rate is also mentioned by Seiler (2000). As a result, with standard and traditional methods the power to detect abnormal performance will be low. Dewan and Ren (2007) study electronic commerce announcements using an event study approach to investigate the effect of announcement on both wealth and risk. In their study, a generalized model which considers systematic and also idiosyncratic risk fluctuations is implemented. Their

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17.Goergen M. and L. Renneboog, 2004, Shareholder wealth effects of European domestic and cross-border takeover bids, European Financial Management 10, 9-45.

results suggest both size and significance of wealth effects is decreased after controlling for risk impact. More precisely, there is no significant wealth effect when simultaneous risk changes are taken into account.

In the same way, Bremer and Zhang (2007) document over event days, short-horizon event-induced abnormal returns and volatility vary significantly and since, volatility is not constant in an event window a test robust to different mean and variance structures should be utilized. Additionally, Wagner (2004) suggests chosen model affects estimated abnormal return considerably. Sonmez (2010) suggests while not all events cause extreme changes in idiosyncratic volatility, merger and acquisition, earnings announcements, CEO changes and law suits are some type of events which induce extreme changes and Brandt et al. (2010) argue stock splits raise idiosyncratic volatility since they mechanically reduce the price. Seiler (2000) argues although event-induced variance is widely witnessed, it is usually ignored in event study's methodology and suggests alternative procedures to be employed in such cases.

To tackle the issue of event-induced volatility in event studies, Boehmer et al. (1991) paper is one of the earliest studies in which an adaptation of the standard methodology is proposed when an event causes increases in variance. They suggest adjustment to the cross-sectional technique. The proposed procedure assumes homogeneous event date variance across all stocks and proportional event date variance to the whole studied period. Savickas (2003) advocates use of a GARCH specification to control for the effect of time-varying conditional volatility throughout event and nonevent windows. Unlike Boehmer et al. (1991) and previous papers, he does not assume similar event volatility effect across different securities and argues the traditional test is misspecified in presence of increasing event-induced variance. Savickas (2003) suggests in GARCH-based model compared to the traditional model, the standardized cross-sectional and the mean rank tests provide more powerful tool to reject false null hypothesis. Wagner (2004) proposes a generalized method to measure abnormal returns (after an initial public offering). The setting is based on modified ARCH-M market model to account for time-variation in idiosyncratic risk as a part that drives conditional abnormal returns. Harrington and Shrider (2007) argue that all events induce variance and this induced

variance make prediction error and biased results for null hypothesis of no mean effect and therefore, probability of true abnormal returns will decrease. They suggest Boehmer et al. (1991) approaches as a suitable alternative and emphasis to always utilize robust standard errors and tests robust to cross-sectional variation.

3. Hypotheses

In this section, in the light of previous literature regarding idiosyncratic volatility and according to research objectives, three hypotheses are developed. Due to the fact that the content of public announcement of company can provide some information regarding firm's specific risk and issues thereof and according to relation between information flow and volatility [18], it is expected to witness significant shift at idiosyncratic volatility level around public announcements. Intuitively, the magnitude of these changes should be different in various categories to which the announcement belongs. Based on Miller's (1977) "divergence of opinion hypothesis" and under short sale constraints, it is expected that after information release dates increases in risk imply higher degree of opinion divergence regarding the stock and that can lead to negative relation between return and idiosyncratic volatility. In addition, finding of Sonmez (2010) that suggests Ang et al's results is driven by significant shifts in idiosyncratic volatility can support this idea that after significant shifts of idiosyncratic volatility as the result of public announcements, a negative relation between return and idiosyncratic volatility could be witnessed. Hence, developed hypotheses are as below:

➢ There are significant differences between idiosyncratic volatility before and after the information release date.

➢ Some type of information can induce more change in idiosyncratic risk after the information release date.

➢ There is a negative relation between idiosyncratic volatility and expected return after information release.

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18. See Bremer and Zhang (2007) and Harrington and Shrider (2007).

4. Methodology

In methodology section all required method to test mentioned hypotheses are introduced. Fama-French model, Paired t-test, Repeated-Measures Designs, One Way ANOVA, EGARCH method, t-test and WLS regressions are explained with respect to each hypothesis.

4.1 Measuring idiosyncratic volatility

Various researches have utilized different methods to measure idiosyncratic volatility. They either have employed total variance, CAPM residuals or Fama French residuals as a proxy for idiosyncratic volatility. According to wide-spread use of the three-factor Fama-French (1993) model in empirical asset pricing literature, it is also employed in this research. Hence, the FF-3 model for stock i would be:

$$R_{iT} - r_t = \alpha_{it} + \beta_{it}(R_{mT} - r_T) + s_{it}SMB_T + h_{it}HML_T + \varepsilon_{iT} \qquad (1)$$

Where T subscript for the day and t for one month (and the fortnight) and ($T \in t$), idiosyncratic volatility for stock i is measured as the standard deviation of the residuals ε_i after estimating above regression using daily data over the given period. So $IVOL_i = SD(\varepsilon_{it})$. Since the efficient market hypothesis assumes immediate reaction of financial markets to pertinent information, shorter-horizon than one month is also examined in this study. However, as it seems inappropriate to run Fama-French model only with five daily observations, one week around the event is not chosen. On the other hand, the minimum of 20 trading days per month is required for each stock around the event to have relatively enough data for two weeks periods.

4.2 Investigating the effect of information release on idiosyncratic volatility

Countless applications of event-study method have been published yet however, in this study standard event-study method is not utilized. Rather it is loosely the paired difference test on differences of the mean of idiosyncratic volatility before and after the given event. According to first objective, idiosyncratic volatility behavior is examined to see whether or not there are significant differences between idiosyncratic volatility before and after the information release date. AS calculated

idiosyncratic volatilities construct matched sample, paired t-test is suitable test to check the significance of differences.

4.2.1 Repeated-Measures Designs

Assumptions of the analysis of variance require having different subjects in the different cells in other words, independent and uncorrelated are synonymous in this context however, where some or all of the cells are not independent another approach called repeated-measures designs is required. As a matter of fact, this procedure partial out effects that causes the dependence (Howell, 2010). Since in this approach blocking carried on each subject to control individual differences among the subjects,   error variance is reduced and there is more precision compared to other approaches and also another advantages is economy of subjects hence fewer subjects are required for the study (Stevens, 2007). However, this approach may provide misleading information if assumptions are ignored. Repeated measures must meet the assumption of normality on each of the individual measures; two other assumptions are homogeneity of variance and sphericity. While homogeneity of variance does require variance of the dependent variable in each group to be equal (if various groups are available) sphericity is regarding equality of variances and correlations among the repeated measures and as Howell (2010) suggests sphericity is assured if we have homogeneity of variance. More details are discussed in result chapter.

In this research, repeated measures belong to the class that compares the same subjects under several different situations and it is illustrated in table 1.

Table 1- Structure of design for Repeated-Measures

One month before	Two weeks before	Two weeks after	One month after
X_{11}	X_{21}	X_{31}	X_{41}
$\vdots$	$\vdots$	$\vdots$	$\vdots$
X_{1n}	X_{2n}	X_{3n}	X_{4n}

Structure of design is presented in table 1, the purpose is to compare all four groups[19] at the same time. To analyze data in the given table model would be $X_{ij} = \mu + TT_i + T_j + TTT_{ij} + e_{ij}$ Where the dependent variable is calculated idiosyncratic volatility for the period, $\mu =$ the grand mean, $TT_i =$ a constant associated with the ith event, representing how much that event differs from the average, $T_j =$ a constant associated with the jth period, representing how much that period mean differs from the average period mean, $TTT_{ij} =$ interaction term to the model, which allows different subjects to change differently over treatments and $e_{ij} =$ the error term. The variables TT_i and e_{ij} are assumed to be independently and normally distributed around zero within each treatment. Also TTT_{ij} to has be normally distributed around zero independently of the other elements of the model. Then F ratios are employed to test null hypothesis which is $\mu_1 = \mu_2 = \mu_3 = \mu_4$

4.3 Examining the effect of category to change idiosyncratic risk

To test second hypothesis initial step is to define change and simply it is defined as relative change, however as only magnitude of change is desirable not the direction, absolute value of the change is utilized to prevent opposite directions negate each other and that would be as:

$$Change = \left|IVOL_{i(t+1)} - IVOL_{it}\right|/IVOL_{it} \quad (2)$$

According to available groups and categories this formula is used to calculate change from two weeks before information release date to two weeks after that and also from one month before to one month after information release date.

4.3.1 One-Way ANOVA

To compare means of different available groups, one-way analysis of variance or abbreviated one-way ANOVA which is generalization of the t test is employed. However, unlike t test one-way ANOVA use the F distribution. This general linear model has two distinct advantages over t test. First, ANOVA imposes no restriction on the number of group, second this procedure allows for simultaneous comparison and to understand interacting effects of two or more variables. This technique's estimates and approximations as well as many others mathematical and statistical model rely on some assumptions have to be met to have reliable results. According

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19. one month before, two weeks before, two weeks after and one month after

to Stevens (2007) normal distribution of observations in each given group on dependent variable is first assumption. Second, observations have to be independent and third one, is homogeneity of variance assumption implies equal variances for the groups. As Howell (2010) has mentioned the logic underlying ANOVA states when all assumptions have met, groups have the same shape and dispersion. Hence, the only way left for them to differ is in terms of their means.

4.4 Examining relation between idiosyncratic volatility and return

To examine relation between idiosyncratic volatility and expected return monthly data and monthly returns are employed. As the risk and return tradeoff should be contemporaneous, it is expected that true relationship is between contemporaneous realized idiosyncratic volatility (denoted by RIVOL) and return. RIVOL it is daily standard deviation of residuals multiplied by the square root of the number of trading days in the month after information release date. One approach to investigate the effect of idiosyncratic volatility on return in this study is to categorize the return based on idiosyncratic volatility and test the mean differences in these groups by employing t-test. Another approach is to assume each announcement as an independent cross-sectional data point and employ regression using following conventional practice which comprise realized return (sum of expected return and random error) as the dependents variable and idiosyncratic volatility as the independent accompanied by other control variables on the other side of cross-sectional regressions.

$$R_{it} = \gamma_{0t} + \gamma_{1t} RIVOL_{it} + \sum_{k=0}^{n} \gamma_{kt} X_{kit} + \varepsilon_{it} \quad (3)$$
$$i = 1,2, \dots, N_t$$

However, beside contemporaneous realized idiosyncratic volatility, it is more desirable to use expected idiosyncratic volatility to examine the relationship with expected return if it is possible. Since expected idiosyncratic volatility (EIVOL) is not observable a suitable model is required to estimate it and it is explained in 4.4.1 section. Hence, the model based on expected idiosyncratic volatility would be:

$$R_{it} = \gamma_{0t} + \gamma_{1t} E_{t-1}[IVOL_{it}] + \sum_{k=0}^{n} \gamma_{kt} E_{t-1}[X_{kit}] + \varepsilon_{it} \quad (4)$$

Where the dependent variable is the realized returns for stock i in period t and $E_{t-1}[IVOL_{it}]$ denotes expected idiosyncratic volatility for time t based on the information set at time $t-1$.

Additionally, since in some papers the relation between lagged idiosyncratic volatility and return is examined, the same procedure and tests for contemporaneous idiosyncratic volatilities is employed for one-month lagged idiosyncratic volatility (LIVOL) to realize whether or not they provide more valuable information.

4.4.1 Estimation of expected idiosyncratic volatility (EGARCH)

Bollerslev (1986) and Taylor (1986) have developed the GARCH model in which the conditional variance is allowed to be dependent upon its previous own lags. Furthermore, asymmetric GARCH models such as GJR and EGARCH are able to model leverage effect in which preceding positive and negative returns have an asymmetric impact on future stock volatility. The advantage of EGARCH models is that even if the parameters are negative σ_t^2 will be positive that avoid imposing artificial restrictions on parameters which can affect the dynamics of the process. Moreover, since this is asymmetric model, θ (sign effect) will be negative when relationship between volatility and returns is negative (Brooks, 2008).

According to Pagan and Schwert (1990) EGARCH is overall the best model among different GARCH models on monthly U.S. stock returns. In addition, Engle and Ng (1993) found EGARCH model captures well the asymmetry of conditional volatilities. Hence, based on some preceding studies (such as Fu (2009)), that suggests idiosyncratic volatility has time-series property and vary substantially over time and also in the light of previous authors (such as Engle and Ng(1993) and Fu (2009),) Nelson's (1991) EGARCH model is employed in this research to estimate expected idiosyncratic volatility as follows:

$$R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \quad (5)$$

$$\varepsilon_{it} \sim N(0, \sigma_{it}^2),$$

$$In\ \sigma_{it}^2 = \alpha_i + \sum_{l=1}^{p} b_{i,l} \ln \sigma_{i,t-l}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \left(\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left[\left| \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - (2/\pi)^{1/2} \right] \right\} \quad (6)$$

Where the conditional variance is a function of the residual variance and return shocks, α_i is long term (return) variance and β_i is weight assigned to period $t - 1$ variance rate $\sigma_{i,t-1}^2$, C_i is the weight assigned to the squared return $\varepsilon_{i,t-1}^2$, θ and γ are the weight of the sign and magnitude effect respectively. Best fitting EGARCH (p, q) model is chosen out of nine different EGARCH models: EGARCH (1, 1), EGARCH (1, 2), EGARCH (1, 3), EGARCH (2, 1), EGARCH (2, 2), EGARCH (2, 3), EGARCH (3, 1), EGARCH (3, 2), and EGARCH (3, 3). Based on Akaike Information Criterion, estimated conditional idiosyncratic volatility (denoted by EIVOL), is used in tests.

5. Data

In this section information regarding gathering and preparing data is provided. Data includes a sample of companies at Helsinki Stock Exchange for the period from January 2004 to December 2011[20]. For companies' announcements NASDAQ OMX Nordic official website (www.nasdaqomxnordic.com) and for other data, DataStream database is used. Moreover, data is analyzed mostly by SPSS and Eviews.

To test the first hypothesis that states there are significant differences between idiosyncratic volatility before and after the information release date, the initial step would be finding appropriate events to calculate idiosyncratic volatility around them. Three criteria are considered for those company announcements: first to prevent overlaps, there should not be any (important) information one month before and one month after the given event to study and the second, due to the fact that it is also aimed to investigate the effect of event type, events that cannot form a group with more ten members are eliminated, third since there are two weeks periods around the announcements the minimum of 20 trading days per month is required for each stock around the event. To find suitable events all companies' announcements of the 60 companies out of the 100 most liquid companies (to prevent possible biases due to infrequent trading) at Helsinki Stock Exchange have been studied from the official website. As the result, 110 announcements in three categories include interim report (69), management change (25) and acquisition (16) are found to continue forward.

AS it is mentioned in methodology section, idiosyncratic volatility for stock i is measured as the standard deviation of the residuals ε_i, estimating three-factor Fama-French (1993) model using daily data over the given period, hence initially it is necessary to have daily Fama-French factors. Papers that study U.S stock market usually use Kenneth French data library[21], however daily Fama-French factors are not available for Helsinki Stock Exchange. In order to have daily factors, various MSCI Finland indexes are utilized and calculations are done for each factor. In addition, it is worth mentioning that IMI index of MSCI Finland which includes large, mid and small cap firms is used as proxy of market (there is very high correlation of

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20. This period is selected to attain relatively symmetric years around the global financial crisis.

21 . See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

OMX Helsinki 25 and this index) and following other papers on Finnish market (such as Virk, 2012), one month interbank offered rate/Bank of Finland (BOF) is used as proxy of risk free rate, so this would be the substitute for one month T-bill return in Fama-French model. Moreover, all data retrieved out of DataStream database. Based on daily returns for different indexes, the next step is simply following calculations:

$$\text{SMB} = \frac{(\text{Small Value} + \text{Small Neutral} + \text{Small Growth})}{3}$$
$$- \frac{(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})}{3}$$

and

$$\text{HML} = \frac{(\text{Small Value} + \text{Big Value})}{2} - \frac{(\text{Small Growth} + \text{Big Growth})}{2}$$

After having announcements selected and Fama-French factors created, idiosyncratic volatility for each four different period (one month before, two weeks before, two weeks after and one month after the information release date) is calculated and hence, for each event four regressions have to be carried out and standard deviation of the residuals ε_i for each one is recorded as idiosyncratic volatility. Usually, each month comprise 22 trading days and 11 trading days is used for two weeks so, half a month is more precise word instead of two weeks. However, before running regressions unit root test (Augmented Dickey-Fuller) for Fama-French factors and stock returns is conducted and it is found that all of them are stationary series (appendix i).

Before continuing forward to conduct the test for the first hypothesis, distribution graph of idiosyncratic volatility in given periods are drawn to be compared to normal distribution and finding outliers (figure 1). Having outlier removed lead to eliminate six events, one out of management change and five out of interim report; however Jarque–Bera test for our groups of different periods indicate that we are far from a normal distribution (appendix ii).
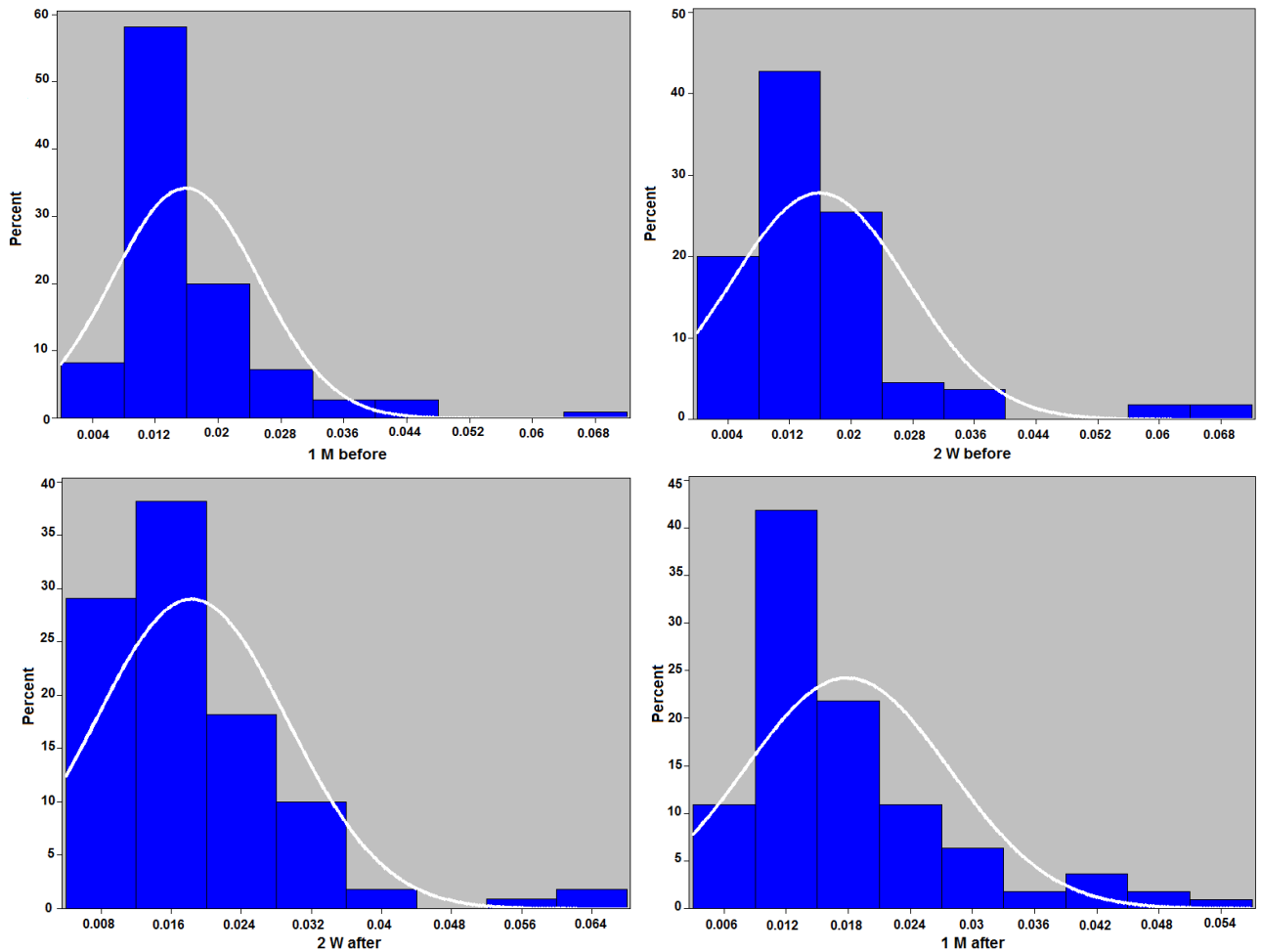
Figure 1- Distribution of Idiosyncratic Volatilities before Removing Outliers

Therefore, to the change shape of distribution nonlinear transformations should be done. Since, nonlinear transformations can make a skewed distribution look more symmetric and reduce the effects of outliers (Howell, 2010) transformations are done after removing outliers. Hence, as a simple and widely used way of transformations natural logarithmic function is employed and as it can be seen in figure 2 that idiosyncratic volatility in each period around information release date have normal distribution so the data is ready for tests to be done regarding first and second hypotheses.
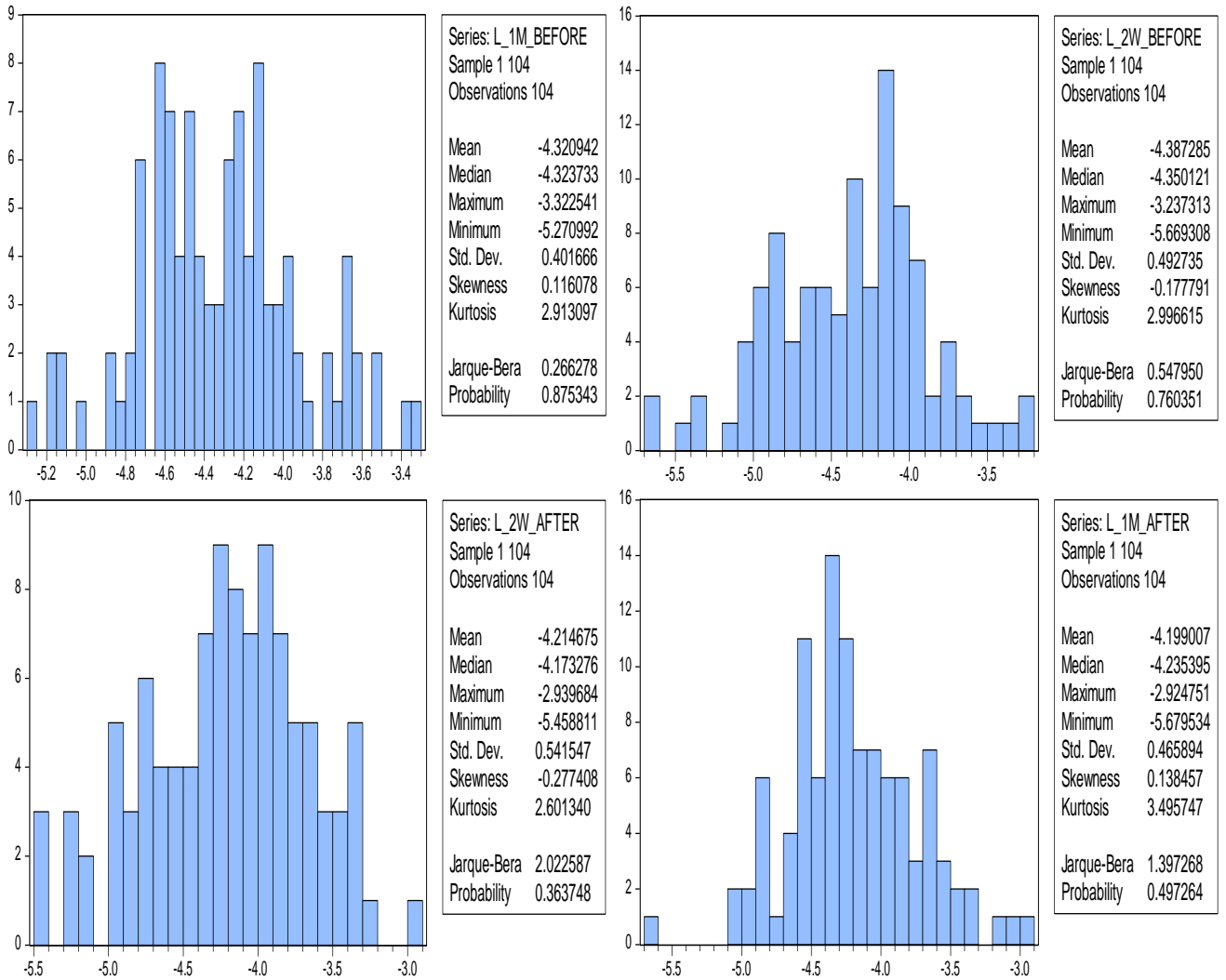
Figure 2-Normality Test after Logarithmic Transformation

To test the third hypothesis and figure out the relation between idiosyncratic volatility and expected return after information release date following variable are employed as described below. The return is continuously compounded return of the stock for one month after public announcement date. Contemporaneous (one month-realized) idiosyncratic volatilities are standard deviation of daily F-F3 residuals over one month after public announcement which are transformed to monthly by multiplying the daily standard deviation by the square root of the number of trading days in that month. The same procedure is employed for one-month lagged idiosyncratic volatility. The estimation of expected idiosyncratic volatility is based on EGARCH method and each model is employed independently for each event. Having at least 30 monthly returns before information release date make the firm eligible for estimation, the EGARCH parameters used to forecast at month t are estimated on

the basis of the data up through month $t-1$ (the sequence is based on past months with respect to announcement day and not regular months sequence). To estimate idiosyncratic volatility the model with the lowest Akaike Information Criterion (AIC) out of nine EGARCH models is chosen. In particular and with respect to the data, there is no dominant best fitting model and EGARCH (1, 1) and EGARCH (3, 3) have the highest proportion with only 15,5% and 14,5% respectively. Additionally, two control variables in the study are the market capitalization as a proxy of firm's size and share turnover as a measure of stock liquidity. To conduct the analysis it is assumed that each public announcement is an independent observation and each observation is treated as an independent cross-sectional data point.

6. Results

This section presents test result, and hypothesis testing process and finding of the research based on performed tests. As a matter of fact, this section includes two sub-sections, idiosyncratic volatility around information release date which is regarding first two hypotheses and the other part, relationship between idiosyncratic volatility and stock return after information release date in which tests for third hypothesis is discussed.

6.1 Idiosyncratic volatility around information release date

As it is mentioned in data part, measured idiosyncratic volatilities have normal distribution after transformation. Therefore, is possible to run repeated-measures designs, paired t-test and one way ANOVA (which all are parametric tests) on the data. Figure 3 demonstrates (mean of) idiosyncratic volatilities in different levels, the figure clearly indicate that around information release date some fluctuation occur and the most paramount shift is from two weeks before announcement date to two weeks after that however repeated measures test reveal whether or not these changes are significant.
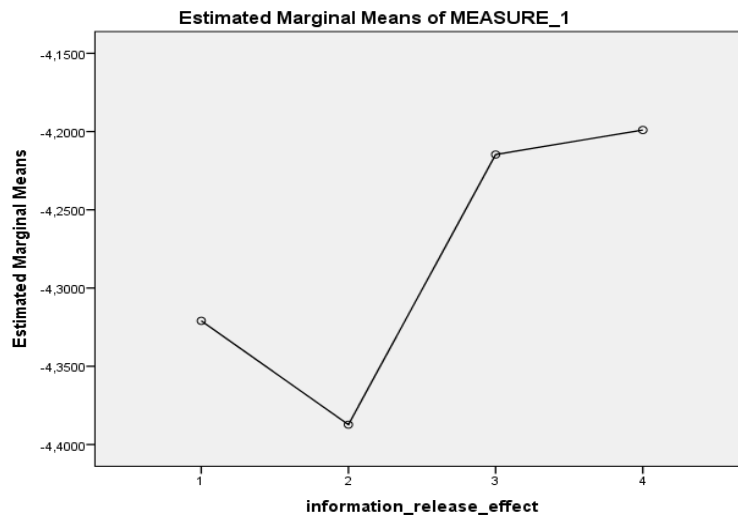
Figure 3- Levels of Idiosyncratic Volatility around Public Announcement

Table 2 provides multivariate tests result regarding information release effect on idiosyncratic volatility. For constructed design all tests (Pillai's Trace, Wilks' Lambda,

Hotelling's Trace and Roy's Largest Root) suggest identical results of rejecting the null hypothesis ($\mu_1 = \mu_2 = \mu_3 = \mu_4$) which states there are significant changes in idiosyncratic volatility. The p value is 0.005 for all tests suggest rejection of the null hypothesis at the 0.05 level. In this case, all four tests have the same Fs and effect size is relatively close to being large (Partial Eta Squared = 0.118). In other words, when a company discloses some specific information to the market, individual firm's specific risk differs. However, multivariate tests should be interpreted in conjunction with univariate tests.

Table 2- Repeated-Measures ANOVA Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
	Pillai's Trace	0.118	4.503[b]	3	101	0.005	0.118
	Wilks' Lambda	0.882	4.503[b]	3	101	0.005	0.118
Information release effect	Hotelling's Trace	0.134	4.503[b]	3	101	0.005	0.118
	Roy's Largest Root	0.134	4.503[b]	3	101	0.005	0.118

a. Design: Intercept Within Subjects, Design: information release effect

b. Exact statistic

Before interpreting results of univariate approach in repeated-measures ANOVA, assumption of the sphericity should be checked. The null hypothesis of the test state the error covariance matrix of the orthonormalized transformed dependent variable is proportional to an identity matrix. However, the p (Sig) value is 0.000 (table 3) and due the fact that Mauchly statistic is significant the null is rejected suggesting violation of the sphericity assumption as it is common. In addition, the epsilon's part of the table 3 in which degree of sphericity is measured, again indicate assumption is violated, being less than one. Whenever the assumption is violated either correcting the univariate approach with the Greenhouse-Geisser (Huynh-Feldt or Lower-bound), utilizing the multivariate approach or the appropriate non-parametric test (Friedman test) should be done.

Table 3-Mauchly's Test of Sphericity[a]

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Information release effect	0.476	75.448	5	0.000	0.659	0.672	0.333

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

   a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

   b. Design: Intercept Within Subjects Design: information release effect

In the next table (table 4), all univariate tests show that information release affect idiosyncratic volatility and that effect results in various levels of volatility with respect to time around release date. However, as Mauchly's test suggests Sphericity Assumed test could not be utilized. Based on Greenhouse-Geisser (7.347,p <0.001), Huynh-Feldt (7.347, p <0.001) and Lower-bound (7.347, p <0.001) F-tests (which would suggest rejecting the null at p <0.05), statistically significant main effects are concluded. In addition, Partial Eta Squared indicates medium level of effect size. Hence, results indicate that volatility is not constant in the event window and the effect is not that small to be ignored.

Table 4- Repeated-Measures Univariate Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Information release effect	Sphericity Assumed	2.497	3	0.832	7.35	0.000	0.067
	Greenhouse-Geisser	2.497	1.978	1.262	7.35	0.001	0.067
	Huynh-Feldt	2.497	2.017	1.238	7.35	0.001	0.067
	Lower-bound	2.497	1.000	2.497	7.35	0.008	0.067
Error(information release effect)	Sphericity Assumed	35.009	309	0.113			
	Greenhouse-Geisser	35.009	203.74	0.172			
	Huynh-Feldt	35.009	207.71	0.169			
	Lower-bound	35.009	103.00	0.340			

Up to now, presented results indicate significant difference in idiosyncratic volatilities occur around the date in which some firm's specific information is announced to the market however, to know where those differences belongs to, paired samples tests are examined. As a matter of fact, pair-wise comparisons table of repeated-measures is not presented due to some unnecessary comparisons and also not providing t statistic (appendix iii) and instead of that, table 5 demonstrates paired samples t-test, in addition to comparison between idiosyncratic volatilities for one month before and one month after announcement dates and also two weeks before and two weeks after the given date that can help to understand whether or not idiosyncratic volatilities level differs significant after the announcement date, two other paired comparisons are conducted. First comparison is between idiosyncratic volatilities levels for two weeks and one month after information release date which can provide a notion regarding how fast market can react to information and digest that. Second comparison would be between one month and two weeks before information release date that can also provide some useful information about information leakage, rumors and insiders dealing before public announcement. According to table 5 paired samples test results for one month before and one month after announcement dates (t=-2.784, p <0.006) and also two weeks before and two weeks after the date (t=-2.903, p <0.005) suggest rejecting null and as alternate states it is concluded there is a significant difference between the means of the idiosyncratic volatility. Hence, public announcement is informative in the way that can change idiosyncratic volatility of the firm. Based on the next pair comparison for two weeks and one month after event (t=-0.420, p <0.675) there is no significant difference between the means of the idiosyncratic volatility which imply that market respond to firm's announcement in shorter period than half a month and after that idiosyncratic volatility remain relatively the same that is compliant with market efficiency. The last pair between one month and two weeks before the event (t=2.121, p < 0.036) show significant difference between two compared periods however, it is not as significant as change in idiosyncratic volatility before and after the announcement. This could hint to information leakage, rumors and insiders dealing before public announcement especially with respect to no significant difference between idiosyncratic volatility for two weeks and one month after event it could not be possible to assume that these differences are driven by previous announcements.

Table 5- Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	1MB - 1MA	-0.12194	0.44673	0.04381	-0.20881	-0.03506	-2.784	103	0.006
Pair 2	2WB - 2WA	-0.17261	0.60643	0.05947	-0.29055	-0.05467	-2.903	103	0.005
Pair 3	2WA - 1MA	-0.01567	0.38008	0.03727	-0.08959	0.05824	-0.420	103	0.675
Pair 4	1MB - 2WB	0.06634	0.31898	0.03128	0.00431	0.12838	2.121	103	0.036

As it was mentioned before the sample comprise, 104 announcements in three different categories include interim report (64), management change (24) and merger and acquisition (16). It is already concluded that in which period idiosyncratic volatility of the company differ with respect to public announcement. However, to figure out that whether or not the magnitude of the change is different in various categories, changes in idiosyncratic volatility according to formula (2) in methodology section is calculated and examined by one way ANOVA between groups. The result of the test is presented in table 7 for four segments changes, changes from two weeks before to two weeks after the event, from one month before to one month after the event, from one month to two weeks before the event and also from two week after to one month after the event. However, the result could be misleading if the assumptions are not met. Since normal distribution and independence of observations are already met, it is required to examine homogeneity of variance assumption which implies equal variances for the groups. Table 6 shows Levene's Test homogeneity of variances in which p-values of all four different defined ($p < 0.249$, $p < 0.137$, $p < 0.137$, $p < 0.711$) segments are not significant therefore; the assumption of homogeneity of variance is met.

Table 6-Test of Homogeneity of Variances- One Way ANOVA

	Levene Statistic	df1	df2	Sig.
Changefor2W	1.408	2	101	0.249
Changefor1M	2.025	2	101	0.137
Changefor2W1MA	0.881	2	101	0.418
Changefor1M2WB	0.342	2	101	0.711

In table 7 result of one way ANOVA between groups is shown. As it can be seen, p values of all different segments (with respect to time around public announcement) are above significance level of 0.05 and null hypothesis ($\mu_{interim\ report}=\mu_{management\ change}=\mu_{acquisition}$) could not be rejected, hence there is no statistically significant difference between change in idiosyncratic volatility driven by interim report, management change and acquisition.

In other words, the category to which the announcement belongs is not important in magnitude of change in idiosyncratic volatility. However, in conjunction with a part of repeated measure ANOVA results, called tests of between-subjects effects presented in table 8 in which differences between announcements are significant (p= 0.000) it can be concluded that the content of announcements themselves are important and not the category of them. An additional test of two way ANOVA without replication also shows that differences between announcements (uncategorized) are significant and also idiosyncratic volatility will change around information release date (appendix iv).

Table 7-ANOVA- One Way ANOVA between groups

		Sum of Squares	df	Mean Square	F	Sig.
	Between Groups	0.006	2	0.003	0.426	0.655
Changefor2W	Within Groups	0.731	101	0.007		
	Total	0.738	103			
	Between Groups	0.020	2	0.010	2.280	0.107
Changefor1M	Within Groups	0.454	101	0.004		
	Total	0.474	103			
	Between Groups	0.005	2	0.002	0.676	0.511
Changefor2W1MA	Within Groups	0.348	101	0.003		
	Total	0.352	103			
	Between Groups	0.001	2	0.001	0.200	0.819
Changefor1M2WB	Within Groups	0.290	101	0.003		
	Total	0.291	103			

Table 8- Repeated-Measures Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	7622.154	1	7622.154	13266.034	0.000	0.992
Error	59.180	103	0.575			

Measure: MEASURE1,Transformed Variable: Average

6.1.1 Tests for sub-samples

After dividing the sample to two equal sub-samples (randomly) and implementing all tests (repeated-measures ANOVA, paired samples t test and one way ANOVA between groups) on each, it is found that both sub-samples support all result of previous tests except the result regarding the significant difference in idiosyncratic volatilities for one month and two weeks before public announcement. To avoid prolixity other tests that support previous results are not shown and discussed. Table 9 provides statistics of paired samples t test for subsamples A and B in details for that given pair. As it can be seen this difference in mean, is only significant for A group (t=2.567, p <0.007) but not for B (t=0.379, p <0.706). Additionally, to recheck the results of sub-samples another two equal random sub-samples are created in which p values for first and second group are 0.07 and 0.06 and they are significant if confidence level is reduced to 90 percent (again all other results are supported). Hence, it is possible to conclude that there are some evidence of insiders dealing, information leakage and rumors before public announcements at Helsinki Stock Exchange which should be considered however, this is not "always" the case and it seems logical.

Table 9-paired samples t test for subsamples

	Mean	Variance	N	Pearson Correlation	df	t Stat	one-tail		two-tail	
							$P(T<=t)$	t_{Crit}	$P(T<=t)$	t_{Crit}
A-L-1M before	-4.280	0.158	52	0.757	51	2.567	0.007	1.675	0.013	2.008
A-L-2W before	-4.397	0.251	52							
B-L-1M before	-4.362	0.164	52	0.783	51	0.379	0.353	1.675	0.706	2.008
B-L-2W before	-4.378	0.239	52							

6.1 Idiosyncratic volatility-return relationship after public announcement

As the initial step to analyze the relation between stock return and idiosyncratic volatility the correlations between them are calculated. The result of correlations between realized return and contemporaneous realized idiosyncratic volatilities (RIVOL), one-month lagged idiosyncratic volatility (L-IVOL) and expected idiosyncratic volatility (E-IVOL) are shown in table 10. As it can be seen, according Pearson Correlation while all measures of idiosyncratic volatility reveal negative correlation with realized return, the only significant correlation is between RIVOL and realized return. On the other hand, the correlation between RIVOL and E-IVOL is 0.34 and significant at the 1% level[22] and the correlation between RIVOL and L-IVOL is 0.43 at the same level. The higher correlation coefficient for L-IVOL rather than E-IVOL with RIVOL could be due to the fact that the change in idiosyncratic volatility level may start from some days before announcement and L-IVOL it is calculated idiosyncratic volatility based on last month daily information (and not estimated based on the sequence of past months with respect to announcement day) and hence L-IVOL can capture more portion of idiosyncratic volatility related to the event at this particular time.

Table 10- Correlations of return, RIVOL, L-IVOL and E-IVOL

		Realized return	RIVOL	L-IVOL	E-IVOL
Realized return	Pearson Correlation	1	-0.275**	-0.153	-0.131
	Sig.		0.005	0.123	0.188
RIVOL	Pearson Correlation	-0.275**	1	0.432**	0.338**
	Sig.	0.005		0.000	0.000
	N	103	103	103	103

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Another employed approach to investigate the idiosyncratic volatility and return relationship is categorizing the return based on idiosyncratic volatility and test the mean differences in these groups. The groups are formed in two different ways, in the first one the sample is divided into terciles and the tercile with the highest

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22. The correlation between RIVOL and E-IVOL is 0.46 in Fu's (2009) study on U.S market in general level and it was expected to witness lower correlation due to the significant jump in idiosyncratic volatility after public announcement which can reduce accuracy of EGARCH estimated volatilities at this specific point.

idiosyncratic volatility is compared to lowest and the second way is to divide them into two groups and compare the groups of above and below average. The results of these comparisons are shown in table 11. The most common feature is that groups with higher idiosyncratic volatility have lower return however; these differences are significant only when they are sorted and categorized based on RIVOL. The comparisons also suggest that the impact is greater and more significant for RIVOL in terciles relative to two groups of above and below average. The mean of return in tercile with low RIVOL is and 0.009929 and in tercile with high -0.04223 and the p-value of t-test is 0.025514 while mean of return in the group which is below average is -0.0001 and in the group which is above average is -0.04246 with the p-value of 0.041948[23]. Moreover, Mann-Whitney Test provides the same result (appendix v).

Table 11- Comparison of return categories based on RIVOL, L-IVOL and E-IVOL

Comparison for high and low groups						
Description	For RIVOL		For EIVOL		For LIVOL	
	Low	High	Low	High	Low	High
Mean	0.009929	-0.04223	-0.00952	-0.02042	0.003769	-0.0195
Variance	0.0027	0.020226	0.013371	0.008491	0.003325	0.012943
t Stat	2.00869		0.42977		1.079356	
P(T<=t)	0.025514		0.3343801		0.142804	
Comparison for above and below average groups						
Description	For RIVOL		For EIVOL		For LIVOL	
	below	above	below	above	below	above
Mean	-0.0001	-0.04246	-0.01504	-0.01572	-0.01403	-0.01712
Variance	0.004726	0.018621	0.01178	0.00763	0.008373	0.012521
t Stat	1.766802		0.03359		0.153659	
P(T<=t)	0.041948		0.48664		0.439093	

The next table (table-12) is summary of regression analysis on relationship between return and RIVOL. The regression analysis is conducted in four models with different

23. Levene's test is used before interpreting t-tests results which imply the equality of variances in compared groups for EIVOL and LIVOL.

control variables (size, turnover and time). As it is mentioned in data section each public announcement is treated as an independent cross-sectional data point and due to the fact that it is impractical to create many dummy variables to control for all these time effects, the time is defined as a dummy control variable in which the data before financial crisis takes the value of 0 if the announcement is before crisis, otherwise 1. The steps for each model are the same and to avoid prolixity only steps for model 1 (m1) is shown in Appendix vi and explained here. To be more exact, at initial step data are pooled and OLS regression is run on the pooled data. The Chow Breakpoint Test is employed to test poolability. P-values of the F-statistic (0.2959), Log likelihood ratio (0.2317) and Wald Statistic (0.2804) in Chow Test imply not to reject poolability. Breusch-Godfrey Serial Correlation LM Test suggest to reject null of autocorrelation (the P-value for F-statistic is 0.1213 and for Obs*R-squared is 0.1142). However, Breusch-Pagan-Godfrey Test shows the presence of heteroskedasticity which is not uncommon in cross-sectional regression. To correct for heteroskedasticity, weighted least square approach in GLS regression is employed. After correction, Breusch-Pagan-Godfrey Test fail to reject the homoscedasticity (the P-value for F-statistic is 0.2591, for Obs*R-squared is 0.2426 and for Scaled explained SS is 0.1385), R-squared increases (from 0.10 to 0.22) and the model become more significant (from 0.005 to 0.001) and even Durbin-Watson stat increases (from 1.58 to 1.81). All the models in table 12 are after correcting for heteroskedasticity and based on GLS. In the model one size is entered as control variable and as it can be seen both size and RIVOL are negatively related to return with relatively close magnitude (-0.239 and -0.202 respectively) and both are significant (p-values are 0.0045 and 0.0005 respectively). In the model two size is changed with share turnover. This variable used to provide some signal regarding both liquidity and updates in investors' forecasts, however this variable is not significant in the model and the magnitude of coefficient for RIVOL remains almost the same and with the p-value being 0.0001. In the third model which both size and turnover are included although the conclusion remain the same with model one and two, the coefficient of RIVOL become larger (-0.29029) with the p-value of 0.0001. Adding time dummy to model three for model four, the result for RIVOL remain approximately constant although in this time size is not significant variable to explain return. According to these models, the relationship between RIVOL and return at this particular time is negative and it is concluded that after public announcement which

is associated with significant shift in idiosyncratic volatility level, the idiosyncratic volatility and return relationship is negative and hence the evidence fail to reject the third hypothesis of this research in which a negative relation between idiosyncratic volatility and expected return after the new information release date, is claimed.

Table 12- Regression analysis of Return and RIVOL

Model	Regression		RIVOL		SIZE		Turnover		TIME	
	R^2	P (F-st)	C	P	C	P	C	P	C	P
M1	0.22813	0.001758	-0.23913	0.0045	-0.20297	0.0005				
M2	0.57825	0.000000	-0.23968	0.0001	-	-	-0.04055	0.4572	-	-
M3	0.31229	0.000489	-0.29029	0.0001	-0.20290	0.0144	0.00491	0.9252	-	-
M4	0.45656	0.000009	-0.29056	0.0000	-0.07180	0.3053	-0.08900	0.1744	0.04806	0.6692

It was also aimed to conduct the regression analysis with the same procedure for EIVOL and LIVOL however, Prob (F-statistic) of regressions reject the significance of models and imply this procedure is not enable us to fit the data (Appendixes vii and viii). In addition, employing ANCOVA as a general linear model imply Lack of Fit Test cannot be rejected and R square is below 0.05 and close to zero, therefore it is concluded that any relationship between return and EIVOL and also between return and LIVOL have occurred by chance and presumably due to significant shift in idiosyncratic volatility after the public announcement these two measures cannot capture the relationship between return and idiosyncratic volatility. Therefore, while RIVOL show negative relation with return after the public announcement, EIVOL and LIVOL do not show any significant effect on return.

6.3 Summary of results and discussion

The first hypothesis assumes "there are significant differences between idiosyncratic volatility before and after the information release date". Over four periods around information release dates which are namely one month before, two weeks before, two weeks after and one month after announcement date, the idiosyncratic volatilities are measured. Employing repeated-measures designs, the results indicate around information release dates idiosyncratic volatility level shift significantly and effect size is relatively close to being large and the most paramount shift is from two weeks before announcement date to two weeks after that. Hence, results fail to reject first hypothesis and this is consistent with papers in which a relationship

between information flow and volatility (Bremer and Zhang, 2007; Harrington and Shrider (2007)) or time-varying behavior for idiosyncratic volatilities is reported. Furthermore, detail analysis based on paired samples t-test reveals some evidence which partially represent information leakage, rumors and insiders dealing before public announcement and on the other hand, idiosyncratic volatilities levels for two weeks and one month after information release date do not change significantly which indicate that market can digest event induced risk in a short period of time and these findings also could imply semi-strong form of market efficiency.

The second hypothesis predicts "some type of information can induce more change in idiosyncratic risk after the information release date". Results of one way ANOVA between groups' tests for three different categories include interim report, management change and merger and acquisition suggest rejecting the hypothesis. Although this is against the developed hypothesis finding is in line with Sonmez (2010) who report "Many of the extreme changes in Ivol from the lowest to the highest quintile are related to merger and acquisition activity (M&A), earnings announcements, CEO changes, law suits and so on" (p.2&3) and presumably no difference is found due to the fact that all these three categories induce extreme change in idiosyncratic volatilities.

The third hypothesis claims "There is a negative relation between idiosyncratic volatility and expected return after the new information release date". Employing t-test and regression analysis reveal negative relation between return and RIVOL. This negative relation may seems to be confusing, however this could be justified through Miller's (1977) "divergence of opinion hypothesis" according to which he does not assume homogeneous expectation and argue under short sale constraints dispersion of opinion leads to stock price overvaluation by optimistic market participants. Since increases in risk imply higher degree of opinion divergence regarding the stock, the negative relation in the study could be justified. On the other hand and based on empirical studies, Sonmez (2010) suggests when significant jumps occurs in idiosyncratic volatility this can derive negative relation between idiosyncratic volatility and return. Since, it is shown that the public announcements are associated with significant shift in firm specific volatility the finding of this study is supported by this idea. Finally, Rachwalski and Wen (2013) document negative

relation between idiosyncratic risk innovations and returns. They explain this negative relation with underreaction and argue since underreaction is temporary this relation only lasts a few months and this is also could be in line with this study. Although this study does not find any significant relationship between EIVOL and LIVOL presumably due to significant jump in idiosyncratic volatility around information release dates, they still can provide some signals regarding future idiosyncratic volatility through the correlation with RIVOL.

7. Conclusion

While the capital asset pricing model (CAPM) suggests that all investors hold the market portfolio in equilibrium, in reality they may not hold perfectly diversified portfolio and hence, they are engaged in idiosyncratic risk. Several papers document idiosyncratic volatility is time-varying and this variation through the time could affect many other issues in finance such as asset pricing models and event studies. Additionally, many attempts have been made to reveal whether or not idiosyncratic risk is priced however, results of recent papers regarding the magnitude and direction of the dependence seem to be contrasting and rather puzzling. Since it is guessed that idiosyncratic volatility is robust around the information release date, it is suitable time to study idiosyncratic volatility. Hence, this research studies behavior of idiosyncratic volatility around public announcement and also idiosyncratic risk and return relationship after information release date.

This study has measured idiosyncratic volatilities over four periods of time around the information release date. The results indicate that firm's volatility is not constant over the examined periods and varies significantly. This event-induced volatility is not small in size and should not be downplayed by event study models. The findings document that it is also possible to witness fluctuations in idiosyncratic volatility even before public announcement presumably due to the existence of information leakage, rumors and insiders dealing however, there is no significant shift in idiosyncratic volatility level from two weeks to one month after announcement dates implying the paramount content in public announcement is digested by market in shorter period that half a month. Additionally, among three analyzed event categories it is found that the category to which the announcement belongs is not important to determine the magnitude of change in idiosyncratic volatility rather; it is the content of announcements which shift volatility level.

Examining the relationship between idiosyncratic volatility and return after public announcement reveal there is a negative relation between contemporaneous realized idiosyncratic volatility and return. In other words, stocks with higher contemporaneous realized idiosyncratic volatility earn lower return after public announcement and it is consistent with "divergence of opinion hypothesis" which

imply assuming heterogeneous expectation and under short sale constraints, dispersion of opinion leads to negative relation between firm's risk and risk-adjusted returns. As significant shift in firm's specific volatility imply higher degree of opinion divergence regarding the stock, it is possible to witness a negative relationship and since divergence of opinion does not last for a long time it is possible to expect this relation as a temporary relationship. Hence, it seems that positive relation between return and idiosyncratic volatility based on under-diversification is inadequate to explain all scenarios. Moreover in this study, the relationships between return and EGARCH estimated idiosyncratic volatility and one-month lagged idiosyncratic volatility are examined. While no significant relation is found between them and return presumably due to significant shift in idiosyncratic volatility level they still can provide some signals regarding future idiosyncratic volatility. Finally, these findings may also provide a useful trading rule for investors with respect to short holding period or long holding period and also portfolio managers should be aware that stock portfolios sorted by idiosyncratic volatility may yield negative or very low return if extreme increase in idiosyncratic volatility occur in significant portion of portfolio, and hence they should continuously monitor and reassess the condition.

7.1 Limitations of the study

A single study cannot provide more than a suggestion and there are limitations that need to be acknowledged and addressed regarding this research. The most paramount limitation of this study is the sample size which may seem not large enough however; in this study there is a trade of between sample size and representativeness of the sample in which it is attempted to make sure that the sample truly represent effect of public announcement by imposing some criteria and that reduce desirable public announcements to be studied. Moreover, this study has focused on Helsinki Stock Exchange and although it possible to generalize the findings, it is not possible to determine the extent to which the findings can be generalized to other markets. Hence, further empirical researches, are required to replicate the study in different contexts and surroundings.

7.2. Future research

Perhaps the first recommendation regarding future research would be replication of this the study in different markets. Moreover, considering relationship between idiosyncratic volatility and return in general and in specific situations such as public announcements in a comparative study also can provide valuable information to understand the nature of idiosyncratic volatility and return relationship and how this relation is possibly distinct in special situations and how different theories can explain different situations. Another study could be performed to see whether idiosyncratic volatility has different components such as expected and unexpected which behave differently with regard to the expected return. In addition, from accounting perspective it is also possible to examine how different practices in accounting such as earning management and income smoothing can affect the shift in idiosyncratic volatility level after public announcement and whether these practices can provide better predictability regarding expected idiosyncratic volatility. Other approach would be employing regime-switching models for prediction of fluctuations in idiosyncratic volatility and to test how well these models work in specific situation and of course there are other various issues to be considered for future researches.

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Appendices

Appendix i: Unit root tests for companies return and Fama-French factors

Null Hypothesis: DAILY_SMB has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=27)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-50.95311	0.0001
Test critical values:	1% level	-3.432644	
	5% level	-2.862439	
	10% level	-2.567294	

   *MacKinnon (1996) one-sided p-values.

Null Hypothesis: DAILY_RM_RF has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=27)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-51.28461	0.0001
Test critical values:	1% level	-3.432644	
	5% level	-2.862439	
	10% level	-2.567294	

Null Hypothesis: DAILY_HML has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=27)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-50.78469	0.0001
Test critical values:	1% level	-3.432644	
	5% level	-2.862439	
	10% level	-2.567294	

| Null Hypothesis: WARTSILA_RETURN has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=27)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-53.26141	0.0001
Test critical values:	1% level	-3.432644	
	5% level	-2.862439	
	10% level	-2.567294	

Appendix ii: Distributions and normality test after removing outliers according to different periods around the events
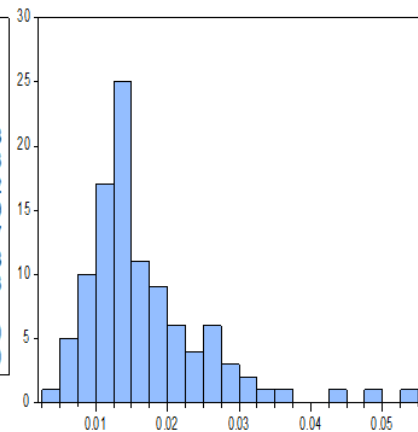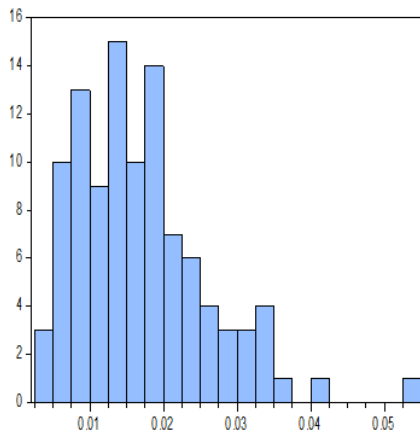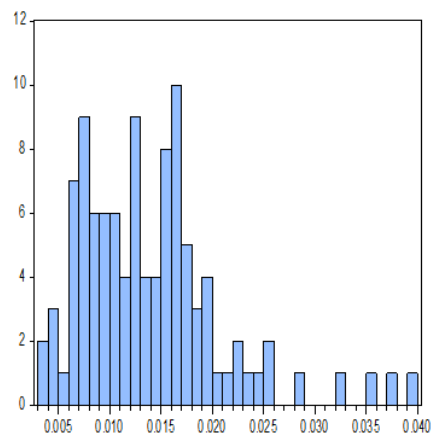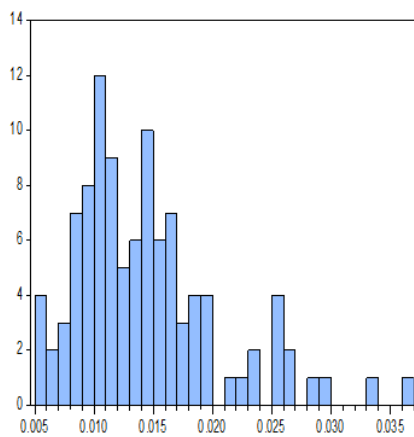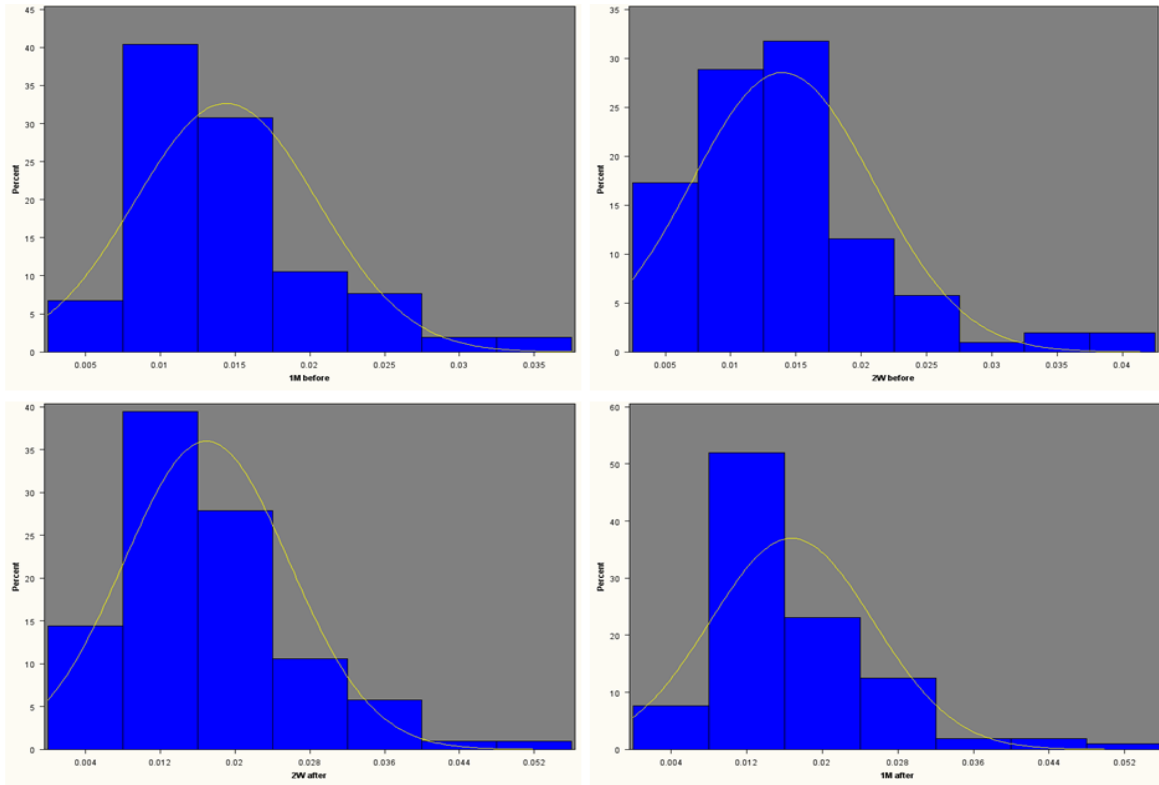
Appendix iii: Pairwise comparisons of Repeated-Measures Designs

Pairwise Comparisons

Measure: MEASURE1

(I) &	(J) informationreleaseeffect	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	0.066[*]	0.031	0.036	0.004	0.128
	3	-0.106[*]	0.052	0.042	-0.209	-0.004
	4	-0.122[*]	0.044	0.006	-0.209	-0.035
2	1	-0.066[*]	0.031	0.036	-0.128	-0.004
	3	-0.173[*]	0.059	0.005	-0.291	-0.055
	4	-0.188[*]	0.051	0.000	-0.289	-0.087
3	1	0.106[*]	0.052	0.042	0.004	0.209
	2	0.173[*]	0.059	0.005	0.055	0.291
	4	-0.016	0.037	0.675	-0.090	0.058
4	1	0.122[*]	0.044	0.006	0.035	0.209
	2	0.188[*]	0.051	0.000	0.087	0.289
	3	0.016	0.037	0.675	-0.058	0.090

Based on estimated marginal means

*. The mean difference is significant at the 0.05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Appendix iv: ANOVA Two-Factor without replication

ANOVA Two-Factor Without Replication

Source of Variation	Sum of Squares	df	Mean Square	F	Sig.	F crit
event	50.75646666	103	0.49278123	3.785722	2.36E-16	1.315369942
informationrelease	2.270273415	2	1.135136708	8.720528	0.000231	3.039722829
Error	26.8146807	206	0.130168353			
Total	79.84142078	311				

Appendix v: Non-parametric comparison of return in different categories according to RIVOL, L-IVOL and E-IVOL

Comparison for high and low groups			
Description	For RIVOL	For EIVOL	For LIVOL
Mann-Whitney U	382.000	516.000	471.000
Wilcoxon W	977.000	1111.000	1101.000
Z	-2.404	-0.760	-1.662
Asymp. Sig. (2-tailed)	0.016	0.447	0.096
Comparison for above and below average groups			
Mann-Whitney U	907.000	1241.000	1143.000
Wilcoxon W	1610.000	2144.000	2089.000
Z	-2.158	-0.268	-0.983
Asymp. Sig. (2-tailed)	0.031	0.788	0.326

Appendix vi: Regression analysis of relationship between return and RIVOL and size

Dependent Variable: REALIZED_RETURN
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RIVOL	-0.366493	0.109831	-3.336895	0.0012
L_SIZE	-0.180622	0.109831	-1.644546	0.1032
C	2.82E-12	0.094396	2.99E-11	1.0000

R-squared	0.100208	Mean dependent var	-5.83E-12
Adjusted R-squared	0.082212	S.D. dependent var	1.000000
S.E. of regression	0.958013	Akaike info criterion	2.780782
Sum squared resid	91.77882	Schwarz criterion	2.857522
Log likelihood	-140.2103	Hannan-Quinn criter.	2.811864
F-statistic	5.568375	Durbin-Watson stat	1.584115
Prob(F-statistic)	0.005095		

Chow Breakpoint Test: 20 50 70
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 1 103

F-statistic	1.214620	Prob. F(9,91)	0.2959
Log likelihood ratio	11.68456	Prob. Chi-Square(9)	0.2317
Wald Statistic	10.93158	Prob. Chi-Square(9)	0.2804

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.155293	Prob. F(2,98)	0.1213
Obs*R-squared	4.339633	Prob. Chi-Square(2)	0.1142

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	13.52067	Prob. F(2,100)	0.0000
Obs*R-squared	21.92402	Prob. Chi-Square(2)	0.0000
Scaled explained SS	39.02357	Prob. Chi-Square(2)	0.0000

Method: Least Squares
Weighting series: RESID
Weight type: Variance (average scaling)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RIVOL	-0.239125	0.080331	-2.976740	0.0045
L_SIZE	-0.202969	0.054080	-3.753137	0.0005
C	0.290937	0.052123	5.581710	0.0000

Weighted Statistics			
R-squared	0.228125	Mean dependent var	0.365235
Adjusted R-squared	0.196620	S.D. dependent var	0.233512
S.E. of regression	0.315171	Akaike info criterion	0.584561
Sum squared resid	4.867319	Schwarz criterion	0.697133
Log likelihood	-12.19859	Hannan-Quinn criter.	0.627719
F-statistic	7.240906	Durbin-Watson stat	1.814432
Prob(F-statistic)	0.001758	Weighted mean dep.	0.256144

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.409150	Prob. F(2,32)	0.2591
Obs*R-squared	2.833007	Prob. Chi-Square(2)	0.2426
Scaled explained SS	3.953108	Prob. Chi-Square(2)	0.1385

Appendix vii: Regression analysis of relationship between return and E-IVOL

Dependent Variable: REALIZED_RETURN
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E_IVOL	-0.085048	0.104554	-0.813431	0.4179
SIZE	0.146371	0.144057	1.016065	0.3121
TURNOVER	-0.231074	0.142396	-1.622755	0.1079
TIME	0.081411	0.221519	0.367511	0.7140
C	-0.057699	0.185198	-0.311552	0.7560

R-squared	0.045068	Mean dependent var	-4.85E-09
Adjusted R-squared	0.006091	S.D. dependent var	1.000000
S.E. of regression	0.996950	Akaike info criterion	2.879093
Sum squared resid	97.40307	Schwarz criterion	3.006993
Log likelihood	-143.2733	Hannan-Quinn criter.	2.930897
F-statistic	1.156275	Durbin-Watson stat	1.560342
Prob(F-statistic)	0.334912		

Appendix viii: Regression analysis of relationship between return and L-IVOL

Dependent Variable: REALIZED_RETURN
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
L_IVOL	-0.136722	0.108536	-1.259688	0.2107
LMC	0.108795	0.148286	0.733682	0.4649
LTURNOVER	-0.228484	0.137949	-1.656295	0.1008
C	-4.59E-09	0.097327	-4.71E-08	1.0000

R-squared	0.053016	Mean dependent var	-4.85E-09
Adjusted R-squared	0.024319	S.D. dependent var	1.000000
S.E. of regression	0.987765	Akaike info criterion	2.851318
Sum squared resid	96.59238	Schwarz criterion	2.953637
Log likelihood	-142.8429	Hannan-Quinn criter.	2.892761
F-statistic	1.847470	Durbin-Watson stat	1.994213
Prob(F-statistic)	0.143514		