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Nonlinear Mean Reversion in Finnish Stock Returns

A Mean Impact Analysis

ACADEMIC DISSERTATION
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Tampere, March 2008

with gratitude

Saikat Sarkar
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Chapter 1

Introduction: Mean reversion in stock returns and market efficiency theory

A generation ago, the efficient market hypothesis was widely accepted by academic financial economists; see, for example, Fama’s (1970) influential survey article Efficient Capital Markets\(^1\). It was generally believed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The accepted view was that when information emerges, the news spreads very quickly and is incorporated into the prices of securities without delay. Thus, neither technical analysis, which is the study of past stock prices in an attempt to predict future prices, nor even fundamental analysis, which is the analysis of financial information such as company earnings and asset values to help investors select undervalued stocks, would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks, at least not with comparable risk.

The weak form of efficient market hypothesis is associated with the idea of a random walk, which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departures from previous prices. The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow’s price change will reflect only tomorrow’s news and will be independent of the price changes today. But news is by definition unpredictable, and resulting price

\(^1\) Fama (1970) distinguishes three types of market efficiency. A market is said to be weak form of efficient if past returns are useless in predicting future returns. A market is semi-strong form of efficient if all publicly available information has in predictable power. A market is fully efficient if all information is reflected in prices, including inside information.
changes must thus be unpredictable and random. As a result, prices fully reflect all known
information, and even uninformed investors buying a diversified portfolio at the tableau of prices
given by the market will obtain a rate of return as generous as that achieved by the experts.

By the start of the twenty-first century, the intellectual dominance of the efficient
market hypothesis had become far less universal. Many financial economists and statisticians have
begun to believe that stock prices are at least partially predictable (see the survey by Malkiel (2003)).
Poterba and Summers (1988) find that the variance ratio test rejects the hypothesis that stock prices
follow a random walk. Fama and French (1988) show that there is significant negative
autocorrelation in long-horizon returns and this finding could be interpreted as evidence of a mean
reversion in stock returns.

Mean reversion in returns means the change of the portfolio return in the direction of a
reversion level as a reaction to a prior change in the portfolio return. After a positive change in the
actual returns, mean reversion causes a negative change at some later point and vice versa. This
reverting move may occur at different speeds, it can eliminate the prior change in, say, one day or in
one year. Intuitively speaking, any force that pushes the price process back to the mean would imply
negative autocorrelation on some time scale and would thus induce the systematic success of
contrarian strategy2 (see DeBondt and Thaler (1987)). This finding spawned the discussion about
whether there is mean reversion in returns or not.

Fama and French (1988) and Poterba and Summers (1988) present corroborating
evidence that $k$-period returns have a time dependent structure consistent with a mean reverting
component in log prices. Fama and French (1988) measure mean reversion by regressing $k$-period
returns on their own lags. Kim, Nelson and Startz (1991) support the findings of Fama and French
(1988) but use a different indirect method, variance ratios. The variance of $k$-period returns scales

2 Contrarian trading strategy means buying recent losers and selling recent winners.
with \( k \). The ratio of the \( k \)-period variance to the 1-period variance can thus be normalized to unity by dividing by \( k \). In case of mean reversion in stock returns, variance ratios typically deviate from unity, then stationary components of stock prices push back these ratios towards unity.

Lo and MacKinlay (1999) find that short-run autocorrelations are not zero and that the existence of too many successive moves in the same direction enables them to reject the hypothesis that stock prices behave as true random walks. There does seem to be some momentum in short-run stock prices. Moreover, Lo, Mamaysky and Wang (2000) also find, through the use of sophisticated nonparametric statistical techniques that can recognize patterns, some of the stock price signals used by technical analysts, such as head and shoulders\(^3\) formations and double bottoms\(^4\), may actually have some modest predictive power.

Economists and psychologists in the field of behavioral finance find such short-run autocorrelation to be consistent with feedback trading strategies\(^5\) (Malkiel (2003)). Individuals see a stock price rising and are drawn into the market in a kind of bandwagon effect\(^6\). For example, Shiller (2000) describes the rise in the U.S. stock market during the late 1990s as a result of psychological contagion leading to irrational exuberance. The behavioralists offer another explanation for patterns

---

\(^3\) Head and shoulders is a technical analysis term used to describe a chart formation in which a stock's price rises to a peak and subsequently declines. Then, the price rises above the former peak and again declines. Finally, the price rises again, but not to the second peak, and declines once more.

\(^4\) Double bottoms is a technical analysis term used to describe a chart in which the price of a security has made two approximately equal bottoms over a period of time. Technical analysts try to buy at one of the bottoms in anticipation of a rise (which would make the shape of a "W" on the chart), opposite to double top.

\(^5\) Feedback trading strategy refers to trading caused by price changes.

\(^6\) The bandwagon effect is the observation that people often do (or believe) things because many other people do (or believe) the same.
of short-run autocorrelation - a tendency for investors to underreact\textsuperscript{7} to new information (Lewellen (2002)). If the full impact of an important news announcement is only grasped over a period of time, stock prices will exhibit the positive autocorrelation found by investigators. Nowadays, behavioral finance becomes more prominent as a branch of the study of financial markets, autocorrelation in returns, as opposed to randomness, as seemed reasonable to many investigators.

Nevertheless, there is a tendency to conclude that evidence of autocorrelation in stock returns constitutes a rejection of market efficiency theory. The Helsinki Stock Exchange (hereafter, HEX) and return\textsuperscript{8} series from eight industry categories are utilized to analyze market efficiency theory based on speculative dynamics\textsuperscript{9}. Portfolio stock returns are used since there may be some distinct characteristics present across industries. The use of more disaggregated data is especially important in the case of the Finnish stock market, where Nokia Corporation (a large telecommunications firm) dominates the aggregate stock market. Furthermore, the Finnish stock market is traditionally dominated by export-oriented, cyclical industries such as Forest, so it would be interesting to study the effect of speculative dynamics on returns in the non-cyclical industrial sectors like Other Services and, Bank and Financial industry categories.

The concept of mean impact curve is introduced to analyze the autocorrelation with the help of conditional mean of stock returns. The mean impact curve is a nonlinear pricing kernel that

\textsuperscript{7} The hypothesis of underreaction states that investors are slow in appreciating good news about a stock, opposite to over-reaction hypothesis.

\textsuperscript{8} Returns are calculated as differences in logarithmic price indices without adjustment dividend, bonus and right issues. Many researchers like Lakonishok and Smidt (1988) and Fishe, Gosnell and Lasser (1993) confirm that their conclusions remain unchanged whether they adjust their data for dividend or not.

\textsuperscript{9} Speculative dynamics means the interaction between different types of traders, some of whom are not rational in the conventional sense of trading on the basis of all publicly available information.
expresses the conditional mean of asset returns as a nonlinear function of the news factors. Lahti and Pylkkönen (1989), Viskari (1992), Järvinen (2000) define news as a given factor like various monetary (for example, real money supply) and macro economic news (for example, change in interest rate). The definition of news by this procedure is questionable because the choice of fundamental economic variables is somewhat arbitrary (see Järvinen (2000)). On the other hand, corporate news also affects the stock market (Damodaran (1985), Vieru, Perttunen and Schadewitz (2006) among others). Therefore, news is defined here as the deviation of actual (released) returns from a market expectation estimate (see Engle and Ng (1993)).

The nonlinear effect of news on conditional mean depends upon the theory of an expectation generating mechanism of stock returns. According to equilibrium pricing models of risky assets, it is possible to express the conditional mean of stock returns as a function of their conditional risk. In this context, the expectation generating mechanism of stock returns follows the dynamic capital asset pricing model developed by Merton (1973). The assumption behind this model is that investors are homogeneous in nature, which is not true for Finnish and other stock markets (see Choe, Kho and Stulz (1999) and Grinblatt and Keloharju (2000)). In this research, the expectation generating mechanism of stock returns is assumed to follow the feedback trading model proposed by Sentana and Wadhwani (1992). It is necessary to specify conditional volatility to estimate the feedback trading model. Standard GARCH (Generalized Autoregressive Conditional Heteroskedasticity), EGARCH (Exponential-GARCH), GJR (Glosten, Jagannathan and Runkle) and WGARCH (Weekend-GARCH) are compared here to select the best fitted volatility model. The best fitted volatility model is used to estimate the feedback trading model.

This research extends the feedback trading model of Sentana and Wadhwani (1992) and Shiller (1984), and is shown to generate a pricing kernel for certain conditional volatility
structures that is a third degree polynomial function of the news factors (Ross (1976), Chen, Roll and Ross (1986), Bansal and Viswanathan (1993), Fama and French (1996), Dittmar (2002)). The relationship between the conditional mean and the news factors is referred to as the mean impact curve (MIC), which provides an extension of the relationship between news and conditional volatility known as the news impact curve proposed by Engle and Ng (1993). As with the news impact curve, the MIC provides a useful framework to identify and test the structure of nonlinearities in the conditional mean of returns. The MIC test statistics are derived within a Lagrange multiplier testing framework, and can be applied as a diagnostic tool to the specification of the model, or as a preliminary test of the nonlinear structure of the raw data.

Applying the framework of the mean impact curve to the Finnish stock market index and several of its components, the empirical results show strong evidence of nonlinear mean reversion in daily equity returns. The empirical results also show that mean reversion is asymmetric with negative returns reverting more quickly to positive returns than positive returns to negative returns.

The organization of the doctoral dissertation is as follows after this introductory chapter. Chapter 2 describes the theoretical arguments of the feedback trading model. Chapter 3 studies the theory of volatility modeling. Chapter 4 illustrates the analysis and testing of the mean impact curve. Chapter 5 describes the information on data sets. The empirical findings of various volatility models are reported in Chapter 6. The mean impact curve is used in Chapter 7 to analyze the nonlinear properties of stock returns in Finland and concluding comments are provided in Chapter 8.
Chapter 2
The feedback trading model: Theoretical arguments for autocorrelated returns

At its most general level, the theory of efficient capital markets is simply the theory of competitive equilibrium applied to asset markets. An important idea in the theory of competitive equilibrium is the Ricardian principle of comparative advantage: England exported cloth to Portugal and imported wine not because England necessarily had an absolute advantage over Portugal in producing cloth, but because England produced cloth comparatively more cheaply than wine relative to Portugal, Ricardo (1817). The same idea is applied in analyzing equilibrium in financial markets, except that comparative advantage is conferred by differences in information held by investors, rather than differences in productivity among producers. The analogy in financial markets of Ricardo’s assertion that absolute advantage is irrelevant is the proposition that information that is universally available cannot provide the basis for profitable trading rules.

It is generally known that if a firm has favorable earning prospects, the theory of efficient capital markets says that the price of the firm’s stock will be bid up to the point where no extra-normal capital gain on the stock will occur when the high earnings actually materialize. Most of the lessons of market efficiency are direct consequences of thinking about financial asset prices as determined by the condition of equilibrium in competitive markets populated by rational agents. When economists define that capital markets are efficient, they are signaling that asset prices are determined by rational agents - that is as being determined as an economic equilibrium. However, the term efficient capital market carries in addition the presumption that
the amount of information which is publicly available, cannot for this reason be used to construct profitable trading rules. This means that, in an efficient capital market, rational agents should have no investment goals other than to diversify to the maximum extent possible so as to minimize idiosyncratic risk, and to hold the amount of risk appropriate to their risk tolerance.

Early works that are directly related to securities analysis as it is now practiced were Williams’ Theory of Investment Value (1938), and Graham and Dodd’s (1934) security analysis, upon which a generation of financial analysts was educated. These put forth the idea that the intrinsic or fundamental value of any security equals the discounted cash flow which that security gives title to, and that actual prices fluctuated around the fundamental values. It is believed that fundamentalists can generate abnormal profit, but Cowles (1933) demonstrates that the recommendations of a major brokerage house, presumably based at least partly on fundamental analysis, do not outperform the market. This implication is that investors who paid for these recommendations are wasting their money. Other clouds shortly began appearing on the horizon. Working (1934) argues that random walks - cumulated series of probabilistically independent shocks - characteristically develop patterns that look like those commonly ascribed by market analysts to stock prices. In his (1934) paper he gives the additional evidence that stock prices follow the random walk hypothesis. Kendall (1953) and Granger and Morgenstern (1963) document that stock prices follow the random walk process and support the idea evinced by Working.

At first the random walk model seemed to flatly contradict not only the received orthodoxy of fundamental analysis, but also the very idea of rational securities pricing. The random walk model seemed to imply that stock prices are exempt from the laws of supply and demand that determine other prices, but instead look more like a casino or a game of musical

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10 The risk that can be potentially eliminated by diversification is called idiosyncratic risk.
chairs that Keynes (1936) chooses as metaphors for the stock market. However, economists immediately realized that such a conclusion was premature.

Roberts (1959) points out that in the economist’s idealized market of rational individuals one would accept exactly the instantaneous adjustment of prices to new information that the random model implies. A pattern of systematic slow adjustment to new information, on the other hand, would imply the existence of readily available and profitable trading opportunities that were not being exploited. Critics of the random walk model can turn the random walkers’ own method of argument back on them: Huge sums of money are spent every year on an activity - securities analysis - which, if the random walk model without drift is correct, should be entirely unproductive. That means that investors are nonetheless irrationally wasting their money year after year employing useless security analysts. If the argument that no behavior inconsistent with rationality and rational expectations can persist in equilibrium is employed, then it must be employed consistently, and this the random walkers were not doing. The continuing existence of large incomes based on generating investment advice is as much a thorn in the side of the random walkers as the failure of this advice to generate extra-normal trading returns is a thorn in the side of fundamentalists.

Resolution to the puzzles pointed out in the previous paragraph required situating the random walk model within the framework of economic equilibrium. Samuelson’s (1965) paper is the first to develop the link between capital market efficiency and martingales. Martingale is a stochastic process in which the conditional expectation of the next value, given the current and preceding values, is the current value. A stochastic process \( x_t \) is a martingale if the best forecast of \( x_{t+1} \) that could be constructed based on current information \( (I_t) \) would just be equal to \( x_t \). On the other hand \( x_t \) is a martingale if and only if \( x_{t+1} - x_t \) is a fair game i.e. the
corresponding forecast of this difference would be zero for any possible value of \( I_r \). Most analysts now consider Samuelson’s to be the most important paper in the efficient capital markets literature because of its role in effecting this shift from the random walk model to the martingale model. The martingale model does not resolve all the puzzles that accompanied the random walk, but it does resolve many of them.

Samuelson (1973) proves that stock prices equal the expected present value of future dividends. The result of Samuelson implies that if fundamentalists are correct in viewing stock prices as equal to discounted expected cash flows, then it follows that future returns are unpredictable, just as the martingale model postulates. Samuelson (1973) also points out that it would be satisfied if the agents have common and constant time preference, have common probabilities, and are risk neutral. If these conditions are satisfied, investors will always prefer to hold whichever asset generates the highest expected return, completely ignoring differences in risk. If all assets are to be held willingly, as must be the case in equilibrium, all must therefore earn the same expected rate of return, equal to the real interest rate. The interest rate, being equal to the constant discount factor, is itself constant over time. Therefore return will follow fair game or, equivalently, prices plus reinvested dividends will follow a martingale process.

In addition to this, if agents do not care what the higher moments of their return distributions are, as risk neutrality implies, they will do nothing to bid away serial dependence in the higher conditional moments of returns. Therefore risk neutrality is consistent with nonzero serial correlation in conditional variances: the fact that future conditional variances are partly forecastable is irrelevant because risk neutrality implies that no one cares about these variances. Engle and Bollerslev (1986) introduce generalized autoregressive conditional heteroskedasticity (GARCH) in a mean model to analyze time varying risk premium in a market of homogeneous
investors. Risk premium of an asset is an increase in the expected rate of return as it becomes more risky. They report that in high volatility periods forecasts of price are less certain and speculation is riskier. Risk premium therefore adjusts to induce investors to absorb the greater uncertainty associated with holding the risky asset. Thus the expected return of an asset goes up as uncertainty increases, which ensures the positive linear relationship between risk and return. Campbell and Hentschel (1992) and French, Schwert and Stambaugh (1987) also report a positive relation between expected return and conditional variance. Other similar studies also suggest a time variation in the relation between risk and return (Harvey (1989), Booth and Koutmos (1998) and Koutmos and Knif (2002)).

Kallunki and Martikainen (1997) document the existence of heterogeneous investors in Finnish stock market and report that the small traders increase their sell orders after the weekend, while large traders are more willing to purchase at the beginning of the week. The presence of heterogeneous investors has been found in prior research on other countries, notably by Choe, Kho and Stulz (1999).

Karhunen and Keloharju (2001) report that in the Finnish stock market the role of foreign ownership has increased steadily over time. Nonprofit institutions have experienced a surge in ownership fraction after January 1999, whereas the ownership fractions of non-financial corporations, finance and insurance institutions, and the government in general have decreased. Grinblatt and Keloharju (2000) find that foreign investors tend to be momentum investors, buying past winning stocks and selling past losers. Domestic investors, particularly the less sophisticated households, tend to be contrarians, selling past winners and buying past losers in the Finnish stock market. Vieru, Perttunen and Schadewitz (2006) extend the result of Grinblatt and Keloharju (2000) and report that earning news triggers trading in every trading class. They
also report that before the event, especially active individuals show increased buying and selling activity compared to the non-event period. After the event, individuals are the most active investor class tends to follow a contrarian strategy, especially selling after the good news. Thus studying risk return relationship in a market of heterogeneous investors has a great deal of importance from the academic and practical point of view, especially in the Finnish stock market.

In addition to this, various researchers document that stock returns are autocorrelated, which can be used as evidence of return predictability. Earlier tests of market efficiency (Fama (1991)) mostly concerned with the forecast power of past returns, this category now covers the more general area of tests for return predictability. Fama (1970) summarizes this earlier work, which largely concludes that the stock market is efficient. However, Cheung, Wong and Ho (1993), on the stock market of Korea and Taiwan, and a World Bank study by Claessens, Dasgupta and Glen (1995), report significant autocorrelation in equity returns from 19 small markets – evidence of return predictability. Similar findings are also documented by Harvey (1995) and Poshakwale (2002) among others. The evidence of return predictability is not uncommon in the Finnish stock market, too (see Berglund and Liljeblom (1988), Knif, Pynnönen and Luoma, (1996)). The feedback trading model of Sentana and Wadhwani (1992) is applied here to analyze autocorrelation in stock returns and at the same time utilized to examine the risk return relationship in a market of heterogeneous investors.

Let us consider a simple model where investors follow different strategies, followed by Sentana and Wadhwani (1992). The demand for shares by the first group is governed by the
risk return relationship. Specifically, the first group will hold a fraction of the shares of the market portfolio given by

$$Q_t = \frac{E_{t-1} R_{s,t} - \gamma_0}{\pi (\sigma^2_{s,t})},$$

(1)

where $Q_t$ represents the fraction of shares held, $R_{s,t}$ is the ex-post return on asset $s$ at time $t$, $E_{t-1} R_{s,t}$ is the corresponding conditional mean of the asset’s return based on information at time $t-1$ of the smart money trader, $\gamma_0$ is the risk free rate of return at which the demand for shares by this group is zero, and $\pi (\cdot)$ represents the asset’s risk, as measured by its conditional volatility $\sigma^2_{s,t}$. In defining the conditional expectations expression, it is assumed that ‘smart’ traders do not take into account any correlation structure arising from nonsynchronous trading. The expression on the right-hand side is effectively the Sharp ratio, although the variance instead of the standard deviation is used in empirical specification, which measures the excess return on the asset adjusted by its risk premium. Smart money traders behave like investors in the optimal-forecast theory: searching for relevant information and incorporating this into prices quickly and smoothly.

The first group (smart money) interacts in complicated ways: it is possible that the first group monitors both the fundamentals and the fashions that will drive noise traders. Investors who are in the first group, attempt to forecast and exploit the behavior of noise traders and occasionally this behavior is too random for risk-averse smart money traders to follow up. But noise traders, who are influenced by fads and fashions, constitute most of the market. In short, investors of the first group trade on information while noise traders operate on noise, trusting noise
is information. In the empirical analysis a linear specification of the risk premium is adopted

\[ \pi \left( \sigma_{x,t}^2 \right) = \lambda \sigma_{x,t}^2 \]  

(2)

where \( \lambda \) is a parameter that controls the strength of the risk-return trade-off, \( \sigma_{x,t}^2 \) denotes the conditional variance of returns in period \( t \) (formed at time \( t-1 \)). A rise in expected volatility increases the risk premium needed to induce smart money to hold all the shares. Note that if all investors had demand functions of the form (1), then market equilibrium \( Q = 1 \) would yield the familiar dynamic-capital asset pricing model (CAPM)

\[ E_{x,t}(R_{x,t}) = \gamma_0 + \pi(\sigma_{x,t}^2) \]  

(3)

\[ R_{x,t} = \gamma_0 + \lambda \sigma_{x,t}^2 + \epsilon_{x,t} \]  

(4)

with \( \gamma_0 \) set to the risk free rate (Merton (1980)). The mean generating process, represented by Equation (4), can be treated as a GARCH in Mean (GARCH-M) process if conditional variance \( \sigma_{x,t}^2 \) follows the GARCH process (see Engle and Bollerslev (1986)). The parameter \( \lambda \) measures the risk premium and the term \( \epsilon_{x,t} \) represents the stochastic error.

Equation (4) can be regarded as an EGARCH-M model, if we allow that conditional variance \( \sigma_{x,t}^2 \) follows the EGARCH (exponential GARCH) process (see Nelson (1991)). Nelson (1991) reports that the estimated risk premium is negatively but insignificantly correlated with conditional variance. Chan, Karolyi, Stulz (1992) also report similar results, while Fama and Schwert (1977), Campbell (1987), Breen, Glosten and Jagannathan (1989), Turner, Startz and Nelson (1989) find a negative relation between the risk and return.

Bollerslev, Chou and Kroner (1992) document the developments in the formulation of ARCH (Autoregressive Conditional Heteroskedastic) models and make an extensive survey of
the earlier literature about the application of volatility modeling in explaining the risk return relationship. Lanne and Saikkonen (2006) address the issue of incorporating the constant term in the GARCH-M model. They document that the inclusion of the intercept term makes the estimate of $\lambda$ vary considerably and changes the sign over time. They found a stable and significantly positive risk-return relationship where the intercept term ($\gamma_0$) was set to be zero.

The second group of investors follows a positive feedback strategy i.e. buys after price increases, so that their demand function is given by

$$Y_t = \theta R_{t,t-1}$$

where positive feedback traders are represented by $\theta>0$, and negative feedback traders represented by $\theta<0$. Negative feedback trading and the role of contrarian trading strategies are studied by Lo and MacKinlay (1990b). Positive feedback trading is not irrational or noise trading in the sense of DeLong, Shleifer, Summers and Waldmann (1990). Such behavior is consistent with that of portfolio insurers and those who use stop-loss orders. This strategy can be entirely rational if preferences exhibit risk aversion that declines rapidly with wealth (see Black (1988 and 1990) and Sentana and Wadhwani (1992) for details). Market equilibrium requires that

$$Y_t + Q_t = 1$$

Now substituting the expression for $Y_t, Q_t$ in the above equation and it becomes

$$E_{t-1} R_{t,t} = \gamma_0 + \lambda \sigma_{\lambda}^2 + \gamma_2 \sigma_{\lambda}^2 R_{t,t-1},$$

where $\gamma_2 = -\lambda \theta$. The term $\gamma_2 \sigma_{\lambda}^2 R_{t,t-1}$ in (7) implies that the presence of positive (negative) feedback trading induces negative (positive) autocorrelation in returns. Moreover, the size of the
autocorrelation in returns is determined by the level of volatility, with higher volatility resulting in greater negative (positive) autocorrelation in returns when there are positive (negative) feedback traders. Intuitively, as expected volatility rises, smart money needs a higher expected return, and this allows a larger deviation of the current price from its fundamental value, which then leads returns to exhibit stronger autocorrelation. The above model suggests that stock price anomalies are larger when the volatility is high.

Autocorrelation in returns may also arise from a variety of reasons unconnected to the feedback trading model. Some authors suggest that autocorrelation may be caused by the interventions of floor specialists in their attempt to maintain orderly markets or by the accumulation of news required by traders in order to enter a transaction (Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980)). Indirect evidence that specialist intervention introduces positive autocorrelation in the daily data is provided by Yamada (1975), who finds that for stocks listed in the first section of the Tokyo stock Exchange where there is no specialist, daily returns are predominantly negatively autocorrelated.

Fama and French (1988), Poterba and Summers (1988) provide the evidence of existence of stationary and random walk component in stock prices. Fama and French (1988) also report that the negative autocorrelation of returns generated by a stationary component is weak at the short return horizons but becomes stronger as the return horizon increases. Another research direction (for example Lewellen (2002)) has tried to explain autocorrelation of stock returns by the behavioral hypothesis but encountered difficulties in finding support for the overreaction and underreaction hypotheses. Time variation of risk premia is another candidate for producing positive autocorrelation (Conrad and Kaul (1988)). Recent research, however suggests that the autocorrelation pattern of stock returns is more complex than commonly
believed. LeBaron (1992) uses a GARCH model with an exponential time varying first order autocorrelation to describe the short run dynamics of several US stock index returns as well as individual stock returns. He reports significant nonlinear first moment dependencies in the sense that autocorrelation and volatility are inversely related. In other words, first order autocorrelations of stock price changes are higher during tranquil periods and lower during volatile periods. This evidence would appear to be consistent with the notion that nonsynchronous trading is the cause of autocorrelation. Taking into account that high trading volume reduces the nonsynchronous trading problem but increases volatility, it is plausible that volatility and autocorrelation are inversely related (see Knif and Pynnönen, (2007)).

Nonsynchronous trading is perhaps the most widely recognized source of positive autocorrelation in portfolio returns. To the extent that nonsynchronous trading is responsible, the autocorrelations are an artifact of the data sampling process and have no economic meaning. Let us set an index of two securities $G$ and $H$ to understand this logic. If the returns on two stocks $G$ and $H$ are independent, but security $H$ trades less frequently than security $G$, then the price of $G$ will respond more quickly when news affecting both stocks arrives. As a consequence, the return on $H$ will appear to respond with a lag to the return on $G$, i.e. there will be a positive cross-autocorrelation. If we now consider an index made up of a large number of securities the positive serial cross-relations will manifest themselves as positive autocorrelation in the index (Sentana and Wadhwni (1992)). Lo and MacKinlay (1990a) show that such positive autocorrelation in an index can be represented by an AR (1) specification for portfolio returns. They also report that in the case of portfolio securities AR (1) coefficient represents the non-trading probability. In the light of the discussion of the feedback trading model, it is important to establish whether and how one could expect any autocorrelation arising from
nonsynchronous trading to vary with volatility of the market. If the high trading volume of an index is an indicator of more trading, then the observed positive correlations between volume and volatility (see Schwert (1990a, 1990b) would suggest that periods of high volatility are also periods when the non-trading effect is small.

On the other hand, one may recall that a period of exceptionally high volatility like the October 1987 crash was characterized by considerable non-trading of securities. Nevertheless, it is possible that the effect of higher volatility could be to reduce the index autocorrelation induced by non-trading. In this setting, the index autocorrelation could in principle fall from a positive number to zero, as the non-trading probability shrinks to zero, whereas in the model with positive feedback traders, the already negative autocorrelation rises in absolute value. Note that models of nonsynchronous trading do not usually predict negative autocorrelation in an index.

Let the error between actual and expected returns be given by

$$\xi_{t,s} = R_{t,s} - E_{t-1} R_{t,s}$$

where $E_{t-1} R_{t,s}$ is defined by (7). To complete the specification of the model, autocorrelation arising from nonsynchronous trading is included into the model by introducing a lagged return term in the mean generating process of $\xi_{t,s}$ (Nelson (1991), Sentana and Wadhwani (1992), and Miller, Muthuswamy, Whaley (1994))

$$\xi_{t,s} = \gamma_1 R_{t-1,s} + \epsilon_{t,s}$$

where $\epsilon_{t,s}$ is a non-autocorrelated disturbance term that measures the “news”, and $\gamma_1 > 0$ is a parameter which captures the positive autocorrelation observed in short horizon returns of
portfolios (Lo and MacKinlay (1990a), Sentana and Wadhwani (1992) and Kadlec and Patterson (1999)). Combining equations (7), (8) and (9) yields a general equation for returns that is a function of lagged returns and conditional volatility

\[ R_{s,t} = \gamma_0 + \lambda \sigma_{s,t}^2 + (\gamma_1 + \gamma_2 \sigma_{s,t}^2)R_{s,t-1} + \epsilon_{s,t} \]  \hspace{1cm} (10)

This model allows for three important channels that affect returns: nonsynchronous trading \((\gamma_1 \neq 0)\), risk premium \((\lambda \neq 0)\), and feedback trading \((\gamma_2 \neq 0)\). According to theoretical specification the sign of the parameter \(\lambda\), which corresponds to the risk premium, should be positive. However, in contrast to this hypothesis, the negative risk return relationship is documented by Fama and Schwert (1977) and Campbell (1987). In general, within a given time period, investors require a larger expected return from a security that is risky. Investors may not require a large premium on average for investing in a security during times when the security is more risky (Glosten, Jagannathan and Runkle (1993)). The parameter \(\gamma_1 > 0\) captures the degree of nonsynchronous trading, and the parameter \(\gamma_2 < 0\) corresponds to the presence of positive feedback trading will generate positive and negative autocorrelation in stock returns respectively.

To complete the specification of the model, it is necessary to specify the form of the conditional volatility \(\sigma_{s,t}^2\), which is discussed in the next chapter. There are various alternative methods to estimate conditional volatility \(\sigma_{s,t}^2\). The most popular method to capture nonlinear dependencies in return series is the Generalized ARCH model proposed by Bollerslev (1986).
Empirically, the family of GARCH (1, 1) models has been very successful (see the survey by Bollerslev, Chou and Kroner (1992)). Thus the procedures developed by Engle and Ng (1993) are followed in this study to select the best fitted volatility model for the Finnish stock market by comparing Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), Glosten, Jagannathan and Runkle (GJR) and Weekend GARCH (WGARCH).
Chapter 3
Modeling and measuring the impact of news on conditional volatility

Uncertainty is central to most modern finance theory. According to asset pricing theories the risk premium is determined by the covariance between the future return on the asset and one or more benchmark portfolios; e.g. the market portfolio or the growth rate of consumption. While it has been recognized for quite some time that the uncertainty of speculative prices, as measured by the variance and covariance, are changing through time (see Mandelbrot (1963) and Fama (1965)), it was not until recently that applied researchers in financial and monetary economics have started explicitly modeling time variation in second or higher-order moments.

The ability to forecast financial market volatility is important for portfolio selection and asset management as well as for the pricing of primary and derivative assets. While most researchers agree that volatility is predictable in many asset markets, they differ on how this volatility predictability should be modeled. In recent years the evidence for predictability has led to a variety of approaches, some of which are theoretically motivated, while others are simply empirical suggestions. The most interesting of these approaches are the asymmetric or leverage volatility models, in which good news and bad news have different predictability for future volatility. These models are motivated by the empirical work of Black (1976), Christie (1982), French, Schwert and Stambaugh (1987) and Nelson (1990).

The importance of a correctly specified volatility model is clear from the range of applications requiring estimates of conditional volatilities. In the valuation of stocks Merton (1980) shows that the expected market return is related to predictable stock market volatility.
French, Schwert and Stambaugh (1987) and Chou (1988) also find empirical evidence for this relationship, although Chou, Engle and Kane (1992) indicate that the relation may be more complex. Ferson and Harvey (1991) provide evidence that much of the predictability of a sample of monthly portfolio returns can be related to the predictability of risk premiums. Schwert and Seguin (1990) and Ng, Engle and Rothschild (1992) show that individual stock return volatility is driven by market volatility, with individual stock return premiums affected by the predictable market volatility.

In the valuation of the stock options, Wiggins (1987) and Hull and White (1987) suggest that stochastic stock return volatility may be the source of some documented pricing biases of the Black-Scholes option pricing formula. Furthermore, the research of Day and Lewis (1992) shows that implied volatility from the Black-Scholes model cannot capture the entire predictable part of future volatility related to some GARCH and EGARCH models. Harvey and Whaley (1992) also find some predictability in changes in implied volatilities, and profit can be earned by trading on this information, although only gross of transaction costs. Amin and Ng (1993) show that option valuation under predictable volatility is different from option valuation under unpredictable volatility. Finally, the predictability of volatility is important in designing optimal dynamic hedging strategies for options and futures (Engle, Hong, Kane (1990)). The predictability of volatility may also affect the results of event studies (see Connolly (1989)).

Given the importance of predicting volatility in many asset-pricing and portfolio management problems, many models of forecasting volatility have been proposed in the literature. Modeling risk of return requires that return has a non-stochastic unconditional mean and variance at each point in time. Of greater relevance to economic agents planning their behavior are the conditional densities of return given all past information. From these densities,
conditional moments can be defined that in general will depend upon the conditioning information set. Letting $R_{t,t}$ be the return of stocks and $I_t$, available at time $t$, $\mu_{t,t}$ and $\sigma_{t,t}^2$ be the conditional means and variances,

$$
\mu_{t,t} = E\left(R_{t,t} \mid I_{t-1}\right) \quad (11)
$$

$$
\sigma_{t,t}^2 = E\left((R_{t,t} - \mu_{t,t})^2 \mid I_{t-1}\right). \quad (12)
$$

Individual economic agents form expectations of return based on their own information sets. If agents know the conditional distribution then they will all have expectations $\mu_{t,t}$ and conditional variance $\sigma_{t,t}^2$. If they differ in their information sets or forecasting models, the expectations may differ.

The autoregressive conditional heteroskedasticity (ARCH) model introduced by Engle (1982) allows the variance of a regression to change over time. The variance in one period is allowed to depend upon variables known from previous periods including the disturbances. The model explicitly recognizes the difference between conditional and unconditional variance; conditional variance may depend upon random variables in the conditioning set, such as past disturbances, while unconditional variance may often be a constant as traditionally assumed. Thus, it may be the case that the Gauss-Markov theorem applies and the ordinary least squares (OLS) is the best linear unbiased estimation, yet an estimator using the ARCH structure such as maximum likelihood will be substantially more efficient (see Engle (1982)).
The ARCH model of $p^{th}$ order can be formulated in terms of information set $I_t$ that includes all information available at time $t$.

$$R_{s,t} | I_{t-1} \sim N(\mu_{s,t}, \sigma_{s,t}^2)$$

$$\mu_{s,t} = \mu_0 + c_1 R_{s,t-1}$$

$$\varepsilon_{s,t} = R_{s,t} - \mu_{s,t}$$

$$\sigma_{s,t}^2 = \alpha_0 + \alpha_1 \varepsilon_{s,t-1}^2 + \alpha_2 \varepsilon_{s,t-2}^2 + \cdots + \alpha_p \varepsilon_{s,t-p}^2$$

The conditional mean of the distribution of returns $\mu_{s,t}$ is specified as a function of past returns. The term $c_1 R_{s,t-1}$ allows for possible autocorrelation due to nonsynchronous trading of the stocks that make up the index. The conditional distribution $N(\mu_{s,t}, \sigma_{s,t}^2)$ is assumed to be normal, with conditional mean $\mu_{s,t}$ and variance $\sigma_{s,t}^2$. The term $I_t$ is the set of all information available at time $t$. In the ARCH model the conditional variance of $\varepsilon_{s,t}$ depends on the realized values of $\varepsilon_{s,t-1}$. If the realized value of $\varepsilon_{s,t-1}$ is large, $E_{s-1}(\varepsilon_{s,i}^2)$ will also be large. There are restrictions on the admissible parameters in $\alpha_i$, $i=0,1,2,3 \cdots p$. First, if any of these parameters are negative, then a single large residual $\varepsilon_{s,t}$ could drive the conditional variance negative. Thus, all $\alpha$ parameters are restricted to be non-negative. Second, if $\alpha$ parameters are too large, then the process will eventually have infinite variance. Third, in many applications, particularly in financial market analysis with linear ARCH (p) model, a long lag length is called for. Due to these problems, an alternative and more flexible lag structure of the ARCH process is provided by Bollerslev (1986).

Bollerslev (1986) generalizes the ARCH process introduced by Engle (1982) to allow for past conditional variances in the current conditional variance equation. This Generalized ARCH (p, q) model called GARCH (p, q) model allows for both autoregressive and
moving average components in the heteroskedastic variance. Bollerslev (1986) formulates the GARCH \((p, q)\) model in the following way:

\[
\sigma^2_{i,t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{i,t-i} + \sum_{j=1}^{q} \beta_j \sigma^2_{i,t-j}
\]

\[
= \alpha_0 + \alpha (L) (\varepsilon^2_{i,t}) + \beta (L) (\sigma^2_{i,t}) \quad (16)
\]

The conditional mean and news or residual term can be calculated by Equations (13) and (14) respectively. To ensure a well defined process all the parameters in the infinite order AR (Autoregressive) representation \(\sigma^2_{i,t} = \kappa (L) (\varepsilon^2_{i,t}) = (1 - \beta (L))^{-1} \alpha (L) (\varepsilon^2_{i,t})\) must be non negative, where it is assumed that the roots of the polynomial \(\beta(\chi) = 1\) lie outside the unit circle (see Nelson and Cao (1992)). It also follows that \(\varepsilon^2_{i,t}\) is covariance stationary if and only if \(\alpha_i + \beta_i < 1\) for GARCH \((1, 1)\) process.

Of course, the GARCH \((p, q)\) model corresponds exactly to an infinite-order linear ARCH model with geometrically declining parameters. An appealing feature of the GARCH \((p, q)\) model concerns the time series dependence in \(\varepsilon^2_{i,t}\). Rearranging terms in Equation (16) is readily interpreted as an ARMA (Autoregressive Moving Average) model for \(\varepsilon^2_{i,t}\) with autoregressive parameters \(\alpha (L) + \beta(L)\), moving average parameters \(-\beta (L)\), and serially uncorrelated innovation sequence \((\varepsilon^2_{i,t} - \sigma^2_{i,t})\). In order to ensure that the conditional variance is always positive, it is necessary to assume that \(\alpha_0\), \(\alpha_1\) and \(\beta_1\) are non-negative fixed parameters. The degree of volatility persistence is measured by \(\alpha_i + \beta_i\) and unconditional variance is given by \(\frac{\alpha_0}{1-(\alpha_1+\beta_1)}\). The degree of persistence means the extent to which conditional volatility is permanent. The existence of unconditional variance requires that volatility persistence is less
than one. Despite the apparent success of these simple parameterizations, the ordinary GARCH model cannot capture the asymmetric impact of shocks on conditional volatility. Moreover, stock returns tend to exhibit non-normal unconditional sampling distributions, in the form of skewness but more pronounced in the form of excess kurtosis (see e.g., Fama (1965)). Black (1976) claims that current return and future volatility are negatively correlated in the leptokurtic distribution of stock return data. A possible economic explanation suggested by Black (1976) and further investigation by Christie (1982) is called leverage effect. According to the leverage effect, a reduction in the equity value would raise the debt-to-equity ratio, hence raising the riskiness of the firm as manifested by an increase in future volatility. As a result, the future volatility will be negatively related to the current return on the stock.

The linear GARCH (p, q) model is not able to capture this kind of dynamic pattern since the conditional variance is linked only to past conditional variances and squared innovations, and hence the sign of returns plays no role in affecting the volatilities. This limitation of the standard GARCH formulation is one of the primary motivations for the EGARCH model developed by Nelson (1991). The EGARCH (p, q) model can be described in the following form

\[
\sigma_{t,t}^2 = \exp \left( \alpha_0 + \sum_{j=1}^q \alpha_j f(z_{s,t-j}) + \sum_{j=1}^q \beta_j \ln \sigma_{s,t-j}^2 \right) \tag{17}
\]

The conditional variance described in Equation (17) is specified as a nonlinear function of past log conditional variances (\(\ln(\sigma_{s,t})\)) and past values of standardized residuals \(z_{s,t}\) where \(z_{s,t} = \frac{\varepsilon_{s,t}}{\sigma_{s,t}}\) is an i.i.d process with \(E(z_{s,t}|I_{t-1}) = 0\) and \(Var(z_{s,t}|I_{t-1}) = 1\) for all \(t\). The function \(f(z_{s,t})\) of the standardized residuals is given by \(f(z_{s,t}) = \left| z_{s,t} \right| - E(\left| z_{s,t} \right|) + \varphi z_{s,t}\), where \(E(\left| z_{s,t} \right|) = \sqrt{\frac{2}{\pi}}\). The
term \( f(z_{s,t}) \) is an asymmetric function of standardized residuals allowing for a magnitude and a sign effect. The term \(| z_{s,t} | - E (| z_{s,t} |)\) represents the magnitude effect and parameter \( \phi \) of \( z_{s,t} \) represents the sign effect. The slope of \( f(z_{s,t}) \) is \( \phi - 1 \) for negative values of \( z_{s,t} \) and for positive values of \( z_{s,t} \) the slope of \( f(z_{s,t}) \) is \( \phi + 1 \). This specification can effectively capture any asymmetric impact of shocks on volatility. The asymmetry can be measured by \( \frac{\phi-1}{\phi+1} \). The volatility persistence implied by Equation (17) is equal to \( \sum_{j=1}^{q} \beta_{s,j} \). The existence of the unconditional variance requires that \( \sum_{j=1}^{q} \beta_{s,j} \) is less than one.

Engle and Ng (1993) document that the EGARCH process overreacts with the news arrival and cannot adequately capture the size effect. Another interesting application of the nonlinear ARCH process is proposed by Glosten, Jagannathan, and Runkle (1993) due to these problems. The GJR (1, 1) model can be written in the following form

\[
\sigma_{s,t}^2 = \alpha_0 + \alpha_1 \varepsilon_{s,t-1}^2 + \phi S_{s,t-1} \varepsilon_{s,t-1} + \beta_1 \sigma_{s,t-1}^2 \quad \text{(18)}
\]

In the conditional variance Equation (18), the asymmetric parameter \( \phi \) is the parameter for the term \( S_{s,t-1} \varepsilon_{s,t-1}^2 \), where the variable \( S_{s,t-1} \), a dummy variable that takes a value of one when \( \varepsilon_{s,t-1} \) is negative and otherwise zero. The asymmetric impact can be measured by \( \frac{(\alpha_1 + \phi)}{\alpha_1} \). In this nonlinear equation \( \alpha_0, \alpha_1 \) and \( \beta_1 \) are constant parameters. Volatility persistence in this model can be measured by regressing \( \sigma_{s,t}^2 \) on a constant and \( \sigma_{s,t-1}^2 \). The parameter of \( \sigma_{s,t-1}^2 \) will measure the persistence in volatility (see Glosten, Jagannathan and Runkle (1993)). Parameter \( \phi < 0 \) in EGARCH and \( \phi > 0 \) in GJR model stands for the leverage effect. That means that volatility tends
to rise in response to bad news (excess return lower than expected) and to fall in response to
good news (excess return higher than expected). Statistically, this effect occurs when bad news
increases predictable volatility more than good news of similar magnitude. Thus the EGARCH
and GJR models allow positive and negative innovations of returns to have different impacts on
conditional variance.

Suppose discount rates are constant and have no relationship to anticipated future
volatility, then any unanticipated decrease in expected future cash flows decreases the stock price
(see Glosten, Jagannathan, and Runkle (1993)). If the variance of the future cash flows remains
the same or does not fall proportionately to the fall in stock prices, the variance of future cash
flows per Euro of stock price will rise and future returns will be more volatile. Hence, if most of
the fluctuations in stock prices are caused by fluctuations in expected future cash flows and the
riskiness of future cash flows does not change proportionally when investors revise their
expectations, then unanticipated changes in stock prices and returns will be negatively related to
unanticipated changes in future volatility. Black (1976) and Christie (1982) suggest a different
reason for the negative effect of current returns on future volatility: a decrease in stock price
changes the capital structure of a firm by increasing leverage. This increase in leverage causes
higher expected variance in the future.

However, it is not yet clear in the finance literature that the asymmetric properties
of variances are due to a change in leverage (Engle and Ng (1993)). It is in this spirit that this
study considers the asymmetric release of information rather than asymmetric information on the
conditional volatility process. The term asymmetric release of information means that
announcement of news is not symmetric during weekdays. In recent years, the presence and
documentation of security price anomalies have been the most puzzling, and consequently most
investigated areas of financial markets research. Since the pioneering works of Fama (1965), many anomalies have been documented concerning the behavior of security returns: some of the most puzzling findings reported in recent years indicate that the distribution of common stock returns varies by day of the week. Most notably, the average returns for Monday are significantly negative. Many researchers like Cross (1973), French (1980), Gibbons and Hess (1981) find negative Monday returns. Keim and Stambaugh (1984) and Linden and Louhelainen (2004) also report that the returns tend to be higher on the last day of the week. This is at odds with asset pricing theories that accommodate neither negative risk premia nor such predictable variations in risk premia. On the other hand Coutts and Sheik (2000) report no evidence of seasonality in stock returns.

Most studies try to explain the day of the week effect with the concept of measurement error or with an issue of specialist related bias over the counter market but Keim and Stambaugh (1984) among others do not support these hypotheses. Lakonishok and Smidt (1988) characterize seasonality of returns as a sample specific bias. Researchers have documented some interesting regularities in trading patterns of individual and institutional investors related to the day of the week, which can partly explain the weekend effect of returns. This issue is first documented by Osborne (1962) and Miller (1988), Lakonishok and Maberly (1990), Kallunki and Martikainen (1997) support Osborne’s hypothesis and report that Monday is the day of lowest activity by institutional investors. Jain and Joh (1988) also report similar evidence and document that 90 percent of total volume on the New York Stock Exchange is traded approximately from Tuesday to Friday.

Another issue of the weekend effect on returns is related to earning and dividend announcements. Pettit (1972), Joy, Litzenberger, McEnally (1977), Watts (1978), Aharony and
Swary (1980) report that earnings announcements provide information to financial markets on the future prospects of the firms. Patell and Wolfson (1982) analyze 1000 earnings announcements and find that good news is more likely to be released when markets are open, while bad news appears more frequently after the close of trading. Damodaran (1989) reports that announcements on Fridays contain more bad news than announcements on other days, especially for earnings reports, and have a negative impact not only on the announcement day but also the following day (which is usually Monday).

Damodaran (1989) also points out that a small portion of the weekend anomalies can be explained by earning and dividend announcements. He also reports that the weekend effect seems to be much stronger and more pervasive to be explained by delayed corporate announcements alone. A larger portion of the weekend effect may be explained by systematic news releases of different institutions such as the Federal Reserve or the Bureau of Labor Statistics. This finding motivates the use of asymmetric release of information in the volatility model. To capture the asymmetric release of information a modification is needed in the standard GARCH (1, 1) process. Franses and Paap (2000) use a similar concept and recommend Periodic Autoregression with Periodically Integrated GARCH (PAR-PIGARCH) model to forecast volatility. They document that the volatility persistence varies on different days of the week with the application of this model. Let us suppose that stock returns are assumed to follow a WGARCH (1, 1) process to analyze asymmetric release of information. The WGARCH (1, 1) model can be written as

\[
\sigma^2_{\text{w}} = \alpha_o + \alpha_1 \varepsilon^2_{t-1} + \phi_1 S^w_{t-1} \varepsilon^2_{t-2} + \phi_2 S^f_{t-1} \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1}
\]

\[
S^w_{t-1} = 1 \text{ when day } t \text{ is Monday otherwise zero.}
\]

\[
S^f_{t-1} = 1 \text{ when day } t \text{ is Friday otherwise zero.}
\]
The conditional variance is specified as a nonlinear function of past conditional variances and news. The effects of Fridays’ and Thursdays’ news are captured by $\varphi_1$ and $\varphi_2$ respectively. The Fridays’ news having an impact on Mondays is captured by $(\alpha_1 + \varphi_1)$. Similarly, the Thursdays’ news affect on Fridays is confined by $(\alpha_1 + \varphi_2)$. If $\varphi_1 > \varphi_2$, then the slope of Mondays’ news impact curve will be steeper than the slope of Fridays’ news impact curve. In this model, $\alpha_0$, $\alpha_1$ and $\beta_i$ represent constant parameters. It is assumed that $\varepsilon_{i,t-1}^2$ and $S_{i,t-1}$, (where $i = m$ or $f$) are approximately independent in the WGARCH (1, 1) model. These two terms $S_{i,t-1}$ and $\varepsilon_{i,t-1}^2$ are independent means on an average Fridays and/or Mondays $\varepsilon_{i,t-1}^2$ is not larger or smaller than other days.

To estimate the parameters $\Omega$ of all these above-mentioned models (i.e. GARCH, EGARCH, GJR and WGARCH), it is necessary to specify the conditional distribution function $\{\mu_{s,t}, \sigma^2_{s,t}\}$. In most applications, a normal distribution is assumed. For lack of a good reason for another distribution, this assumption is adopted here, although the models are flexible enough to admit other laws. In general, given a sample of daily returns $R_1, R_2, \cdots R_T$ and initial values $R_0, \varepsilon_{s,t}, \sigma_{s,t}$ for $t = 0, 1, 2, \cdots, r = \max(p, q)$, the log likelihood function is then given by

$$L(\Omega | p, q) = \sum_{t=r} \ln f(R_{s,t}, \mu_{s,t}, \sigma^2_{s,t})$$

where $f(R_{s,t}, \mu_{s,t}, \sigma^2_{s,t})$ is the normal density function and $\Omega$ the vector of unknown parameters. Maximization of $L(\Omega | p, q)$ gives the maximum likelihood estimates of the parameters. The values of $p$ and $q$ need to be pre specified. The likelihood function can be maximized for several combinations of $p$ and $q$, and the maximum values can be compared statistically to obtain the
optimal order of the process. Since the log likelihood function is highly non-linear in the parameters, numerical maximization techniques have to be used to estimate this process. The method of estimation adopted in this research is based on the Berndt, Hall, Hall and Hausman (1974) algorithm.

ARCH class models have usually been the best for modeling the conditional heteroskedasticity of daily returns. However, the ARCH models do not seem to work at all in modeling the intraday returns. This is due to the systematic periodical structure of volatility in the course of a day that ARCH models fail to consider. This kind of systematic periodicity is the reason for the failure of modeling intraday returns with ARCH models (Andersen and Bollerslev (1997)). The assumptions of ARCH models require the rapid reduction of the autocorrelation structure. The GARCH models can deal better with the persistence of the autocorrelation, but they cannot work with this kind of periodicity either. It is necessary to filter the intraday dynamics from the returns (Martens, Chang and Taylor (2002)) to be able to use GARCH models.

Various kinds of ARCH models have been used to estimate the conditional volatility of daily returns in this research. It is hard to compare the amount of persistence in variance that these models predict, because the parameterization of the models differs so much. One way to compare persistence in variance across models is to regress $\sigma_t^2$ on a constant and $\sigma_{t-1}^2$. The parameter of $\sigma_{t-1}^2$ will measure the volatility persistence (see Glosten, Jagannathan and Runkle (1993)).

A comparison between the GARCH (1, 1), EGARCH (1, 1), GJR (1, 1) and WGARCH (1, 1) suggests an interesting metric by which one can analyze the effect of news on conditional volatility. The empirical literature on the impact of news on volatility has been
greatly expanded in recent decades. The earlier studies in the 1980s used daily return data and simple regressions and do not obtain very promising results (Aggarwal and Schirm (1992)). Since the 1990s the availability of high frequency data, numerous variations of GARCH models and the methods of filtering intraday volatility periodicity and other market anomalies (Andersen and Bollerslev (1997)) have enabled the better testing of the impact of news on volatility. Researchers have taken news as a given factor, like some macro economic news announced by some authorities (public or private) in this category of research. They categorized the news in three forms:

1. **Conflicting news;** the news moments which gave conflicting information on the state of the economy i.e. both the positive and the negative news.

2. **Consistent news;** the news moments which gave consistent information on the state of the economy i.e. either the positive or the negative news.

3. **No surprise news;** the news that does not surprise markets should not have any effect on asset prices, since the prices have already taken the information into account.

Earlier studies show that the macro announcements seem to have the greatest impact on bond markets and weak impact on stock markets (Andersen, Bollerslev, Diebold and Vega (2004)). Nikkinen and Sahlström (2004) have documented that U.S macroeconomic news announcements are valuable sources of information on European stock markets while domestic news releases seem to be unimportant. Laakkonen (2004) has also documented that conflicting news was found to increase stock market volatility significantly more than consistent news. News can also be defined as the deviation of actual (released) figures from a market expectation estimate (Engle and Ng (1993)). It has already been mentioned that the conditional expected mean and the
The conditional variance of returns are \( \mu_{s,t} = E(R_{s,t} | I_{t-1}) \) and \( \sigma^2_{s,t} = Var(R_{s,t} | I_{t-1}) \) respectively. Given these definitions, the unexpected return at time \( t \) is \( \varepsilon_{s,t} = R_{s,t} - \mu_{s,t} \). In this research, the error term or unexpected return \( \varepsilon_{s,t} \) is treated as a collective measure of news at time \( t \) (Engle and Ng (1993)). A positive \( \varepsilon_{s,t} \) (an unexpected increase in price) suggests the arrival of good news, while a negative \( \varepsilon_{s,t} \) (an unexpected decrease in price) suggests the arrival of bad news. Further, a large value of \( |\varepsilon_{s,t}| \) implies that the news is significant or big in the sense that it produces large unexpected change in price.

Holding constant the information dated \( t-2 \) and earlier, it is possible to examine the relationship between \( \sigma^2_{s,t} \) and \( \varepsilon_{s,t-1} \). Engle and Ng (1993) call this news impact curve, with all lagged conditional variances evaluated at the level of the unconditional variance of the stock return, the news impact curve, because it relates past return shocks (news) to current volatility. This curve measures how new information is incorporated into volatility estimates.

The news impact curve of the GARCH (1, 1) model can be written as

\[
\sigma^2_{s,t} = A + \alpha \varepsilon^2_{s,t-1}, \quad \text{where} \quad A = \alpha_0 + \beta \sigma^2.
\]  

(20)

Unconditional variance can be found by

\[
\sigma^2 = \frac{\alpha_0}{1 - (\alpha + \beta)}.
\]
The term $A$ is a constant. Equation (20) also tells us about the symmetric impact of news on conditional volatility. This curve is a quadratic function centered at $\varepsilon_{s,t-1} = 0$. In this model $\sigma^2$ represents the unconditional volatility and the existence of unconditional volatility requires that volatility persistence is less than one ($\alpha_i + \beta_i < 1$). Similarly the news impact curve of the EGARCH (1, 1) model can be written as

$$
\sigma_{t,t}^2 = A \exp \left[ \alpha_1 \left( \frac{1 + \varphi}{\sigma} \right) \varepsilon_{s,t-1} \right], \text{ when } \varepsilon_{s,t-1} \geq 0
$$

(21)

$$
\sigma_{t,t}^2 = A \exp \left[ \alpha_1 \left( \frac{\varphi - 1}{\sigma} \right) \varepsilon_{s,t-1} \right], \text{ when } \varepsilon_{s,t-1} < 0
$$

(22)

where $A = \exp \left( \alpha_0 - \alpha_1 \sqrt{2/\pi} \right) \sigma^{2^{\beta_i}}$.

The condition for the existence of unconditional variance is as follows:

$$
E \left( \ln \left( \sigma_{s,t}^2 \right) \right) = \frac{\alpha_0}{1-\beta_i}, \text{ where } \beta_i < 1
$$

Equation (21) and (22) represent the news impact curve of the EGARCH model. Both curves have their minimum value at $\varepsilon_{s,t-1} = 0$ but increasing exponentially with different parameters. Thus the EGARCH model captures the asymmetric impact of news on volatility. The term $\sigma^2$ represents the unconditional volatility and the existence of unconditional volatility requires ($\beta_i < 1$). The news impact curve of the GJR model can be written as

$$
\sigma_{t,t}^2 = A + \alpha_1 \varepsilon_{s,t-1}^2, \text{ when } \varepsilon_{s,t-1} \geq 0
$$

(23)

$$
\sigma_{t,t}^2 = A + \left( \alpha_1 + \varphi \right) \varepsilon_{s,t-1}^2, \text{ when } \varepsilon_{s,t-1} < 0
$$

(24)

where $A = \alpha_o + \beta_1 \sigma^2$.
Like the EGARCH model, the GJR model also captures the asymmetric impact of news on volatility. The parameterizations of the news impact curve, represented by Equations (23) and (24), are different from the EGARCH model. The constant term and the unconditional volatility are represented by $A$ and $\sigma^2$ respectively. Glosten, Jagannathan and Runkle (1993) assumed that $S_{i,t-1}$ and $\varepsilon^2_{i,t-1}$ are uncorrelated in the GJR (1, 1) model i.e. the size and sign (positive or negative) of shocks are independent.

The news impact curves of the WGARCH (1, 1) model are Otherdays’ news impact curve, Mondays’ news impact curve and Fridays’ news impact curve. Otherdays’ news impact curve can be written as

$$\sigma^2_{i,t} = A + \alpha_1 \varepsilon^2_{i,t-1}$$

(25)

Mondays’ news impact curve is given by

$$\sigma^2_{i,t} = A + (\alpha_1 + \varphi_1)\varepsilon^2_{i,t-1}$$

(26)

Fridays’ news impact curve then is specified by

$$\sigma^2_{i,t} = A + (\alpha_1 + \varphi_2)\varepsilon^2_{i,t-1}$$

(27)

where $A = \alpha_0 + \beta_0 \sigma^2$ and parameter $\alpha_0$ is the constant term and $\sigma^2$ is the unconditional variance. According to this model Otherdays’ news impact curve, Mondays’ news impact curve and Fridays’ news impact curve are represented by Equations (25), (26) and (27) respectively. Here $A$ is the constant term. The following conclusions can be drawn from the above analysis of four
different volatility model specifications and these are

1. GARCH and WGARCH fail to capture the asymmetric impact of shocks on conditional volatility. The news impact curve of the nonlinear model of Engle and Bollerslev (1986) is symmetric for positive and negative shocks and passes through the origin. The WGARCH model captures the asymmetric release of information by allowing a different slope of the news impact curves for different days of the week.

2. EGARCH and GJR capture the asymmetric impact of news on conditional volatility. The news impact curves of these asymmetric volatility models capture the leverage effect by allowing different slopes for bad news and good news.

3. The news sensitivity of different indices can be measured by the steepness of the news impact curve. The steeper the news impact curve the higher the news sensitivity.

These differences between the news impact curves of the models have important implications for portfolio selection and asset pricing. For instance, after a major unexpected price drop, like the 1987 crash, the predictable market volatility given by the GARCH and EGARCH are very different, as implied by their news impact curves. Since the predictable market volatility is related to market risk premium, the two models imply very different market risk premium, and hence different risk premiums for individual stocks under a conditional version of the capital asset pricing model. The news impact curve is a convenient way to summarize the effect of news on volatility implied by a parametric model of predictable volatility. By comparing the news impact curve of alternative predictable volatility models, it is possible to highlight the differences between the models. By testing whether the news impact curve of model offers a good fit to the data, one can understand the quality of the model. The diagnostic tests of news impact curve for
different volatility models are the sign bias test, the negative size bias test, and the positive size bias tests. These tests examine whether we can predict the squared standardized residual by some variables observed in the past which are not included in the volatility model being used. If these variables can predict the squared standardized residual, then the variance model is misspecified. The sign bias test considers the variable $S_{t,t-1}$. This test examines the impact of positive and negative return shocks on volatility not predictable by the model under consideration. The negative size bias test utilizes the variable $S_{t,t-1} \epsilon_{t,t-1}$. It focuses on the different effects that large and small negative return shocks have on volatility which is not predicted by the volatility model. The positive size bias test utilizes the variable $S_{t,t-1}^+ \epsilon_{t,t-1}$, where $S_{t,t-1}^+$ is defined by $1-S_{t,t-1}$. It focuses on the different impacts that large and small positive return shocks may have on volatility and which are not explained by the volatility model. Since an important piece of bad news may have a different impact on volatility than an important piece of good news, it is critical to distinguish between positive and negative return shocks while examining the effects of the magnitude of a piece of news.

The above discussion suggests that the optimal forms of the regressions for conducting the sign bias test, the negative size bias test, the positive size bias test are respectively,

\begin{align}
z_{t,t}^1 &= a + b \ S_{t,t-1} + \epsilon_{t,t} \\
z_{t,t}^2 &= a + b \ S_{t,t-1} \epsilon_{t,t-1} + \epsilon_{t,t} \\
z_{t,t}^3 &= a + b \ S_{t,t-1}^+ \epsilon_{t,t-1} + \epsilon_{t,t}
\end{align}

where $a$ and $b$ are constant parameters, $z_{t,t}^1$ is the squared estimated standardized residuals. The term $\epsilon_{t,t}$ represents the residual at time $t$. The sign bias test statistic is defined as the $t$ ratio for
the parameter $b$ in the regression Equation (28). The negative size bias test statistic is defined as the $t$ ratio of the parameter $b$ in the regression Equation (29). The positive size bias test statistic is defined as the $t$ ratio of the parameter $b$ in the regression Equation (30). To construct these tests jointly

\[ z_{s,t}^2 = a + b_1 S_{s,t-1} + b_2 S_{x,t-1} e_{s,t-1} + b_3 S_{x,t-1} e_{s,t-1} + e_{s,t} \]  \hspace{1cm} (31) \]

where $a$, $b_1$, $b_2$, and $b_3$ are the constant parameters and $e_{s,t}$ is the residual at time $t$. The $t$ ratios for $b_1$, $b_2$, and $b_3$ are the sign bias, the negative size bias and the positive size bias test statistics respectively. The joint test is the LM (Lagrange multiplier) test for adding the three variables in the variance equation. The test statistic is equal to $T$ times the R squared of this regression. If the volatility model being used is correct, then $b_1 = b_2 = b_3 = 0$ and $e_{s,t}$ follows $i.i.d$. Thus the $t$ statistics and the LM statistic have the standard limiting distributions. In particular, the LM test statistic follows a chi-square distribution with three degrees of freedom.
Chapter 4
Analysis and testing of the mean impact curve

This chapter consists of two parts. The derivation of the mean impact curve is described in Part 4.1 and Part 4.2 describes testing the mean impact curve.

4.1 Derivation of the mean impact curve

An important characteristic of the feedback trading model in Equation (10) is the role of volatility $\sigma^2_{t,t}$, in determining expected returns at time $t$, defined as,

$$
\mu_{s,t} = \gamma_0 + \gamma_1 R_{s,t-1} + \lambda \sigma^2_{t,t} + \gamma_2 \sigma^2_{t,t} R_{s,t-1}
$$

This suggests that news $\epsilon_{s,t}$, can affect the conditional mean through two channels: the direct effect of news on $R_{s,t-1}$, and the indirect effect via the conditional variance $\sigma^2_{t,t}$.

To highlight the relationship between the conditional mean and the news, consider the simplest representation of volatility given by the ARCH (1) model of Engle (1982)

$$
\sigma^2_{t,t} = \alpha_0 + \alpha_1 \epsilon^2_{t,t-1}
$$

For this volatility structure, the conditional mean in (32) becomes

$$
\mu_{s,t} = \gamma_0 + \lambda \alpha_0 + (\gamma_2 \alpha_0 + \gamma_1) \mu_{s,t-1} + (\gamma_1 + \gamma_2 \alpha_0) \epsilon_{t,t-1} + (\lambda \alpha_1 + \gamma_2 \alpha_1 \mu_{s,t-1}) \epsilon^2_{t,t-1} + \gamma_2 \alpha_1 \epsilon_{t,t-1}^3
$$

* This chapter is used in Nonlinear mean reversion in stock returns: Mean impact curve estimates for Finland, conference paper, co-authored with Antti J. Kanto and Vance L. Martin, presented in Atlanta Federal Reserve Bank, USA.
where the definition of lagged returns \( R_{t-1} = \mu_{t-1} + \varepsilon_{t-1} \), is also used. This expression shows that the conditional mean \( \mu_{t} \) is a cubic equation in the “news” variable \( \varepsilon_{t-1} \). This expression has a structure similar to the nonlinear pricing kernel models of Bansal and Viswanathan (1993) and Dittmar (2002).

The form of the relationship between \( \mu_{t} \) and \( \varepsilon_{t-1} \) is determined by the parameters of the feedback trading model and the conditional volatility parameters. Following Engle and Ng (1993), who introduced the concept of the news impact curve (NIC) by plotting the relationship between \( \sigma_{t}^{2} \) and \( \varepsilon_{t-1} \), the relationship between \( \mu_{t} \) and \( \varepsilon_{t-1} \) is referred to as the mean impact curve (MIC).

Some examples of the MIC for alternative specifications of the feedback trading model are given in Figure 1, which are based on the parameterizations:

<table>
<thead>
<tr>
<th>Mean impact curves</th>
<th>Parameters ( \gamma_0 )</th>
<th>( \gamma_1 )</th>
<th>( \lambda )</th>
<th>( \gamma_2 )</th>
<th>( \alpha_0 )</th>
<th>( \alpha_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIC-1</td>
<td>0.1</td>
<td>0.3</td>
<td>-0.1</td>
<td>-0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-2</td>
<td>0.1</td>
<td>0.0</td>
<td>-0.1</td>
<td>-0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-3</td>
<td>0.1</td>
<td>0.3</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-4</td>
<td>0.1</td>
<td>0.3</td>
<td>-0.1</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

The first model MIC-1 represents the most general model with all three channels of the feedback trading model operating. This model serves as the benchmark for all of the other models considered here. The remaining three models exclude respectively nonsynchronous trading (MIC-2), smart money trading (MIC-3), and feedback trading (MIC-4). The MIC-1 model exhibits a positive relationship locally near \( \varepsilon_{t-1} = 0 \), between the conditional mean and news. This relationship is dominated by the positive effect of nonsynchronous trading on portfolios.
Figure 1: Mean impact curves of alternative models (MIC-1, MIC-2, MIC-3, MIC-4), based on the ARCH (1) conditional variance: MIC-1 is the benchmark model that contains all three trading channels. The equation for the benchmark model is

\[ \mu_t = \gamma_0 + \lambda \alpha_t + (\gamma + \gamma_2 \alpha_t) \mu_{t-1} + (\gamma_1 + \gamma_2 \alpha_t) e_{t-1} + \epsilon_{t-1} + \gamma \alpha_{t-1} \epsilon_{t-1} + \gamma_2 \alpha_{t-1} \epsilon_{t-1} \]

where the term \( \mu_t \) is the expected return at time \( t \) and \( e_{t-1} \) is the unpredictable return at time \( t-1 \). The term \( \gamma_0 \) is the risk free rate of return, the parameter \( \lambda \) measures the risk premium. The parameter \( \gamma_1 \) corresponds to nonsynchronous trading, \( \gamma_2 \) represents positive feedback trading. The parameters \( \alpha_0, \alpha_t \) are in the ARCH (1) variance process. The shape of the above MIC-1 is indicative of cases with \( \gamma_0 = 0.1, \gamma_1 = 0.3, \lambda = -0.1, \gamma_2 = -0.1 \) and \( \alpha_0 = 0.1, \alpha_t = 0.1 \). MIC-2 excludes nonsynchronous trading. MIC-3 excludes smart money trading. MIC-4 excludes feedback trading.

For larger news shocks, the negative effect of smart money (\( \lambda < 0 \)) and positive feedback trading effect (\( \gamma_2 < 0 \)), start to dominate the positive autocorrelation arising from nonsynchronous trading. For very large news shocks the effects of a positive shock on the conditional mean at
time $t$ is now negative, that is, there is mean reversion. This is an important feature of the model as it helps to explain the phenomena that returns tend to exhibit positive correlation (mean aversion in asset prices) for short horizons, but negative correlation (mean reversion in asset prices) for longer horizons (Fama and French (1988), Kim, Nelson and Startz (1991)). If relatively small shocks represent short horizons, then a positive shock at $t-1$, that results in a positive conditional mean at time $t$, results in positive autocorrelation in returns. Now suppose that there is a sequence of positive shocks, such that the size of the cumulated shocks over an extended period is also positive. From the mean impact curve schedule, this now corresponds to a large shock which may result in a negative conditional mean and hence negatively correlated returns\footnote{This behavior is symptomatic of asset bubbles, where there is a sequence of positive asset returns during a bullish market, followed by a very large negative return when the bubble bursts as the market corrects itself.}.

The effect of increasing trading frequency on the mean impact curve is highlighted by MIC-2 in Figure 1, where the effects of nonsynchronous trading on the shape of MIC-1 are eliminated. The MIC-2 schedule is now downward sloping everywhere with a point of inflexion near $\epsilon_{t,t-1} = 0$, a positive (negative) shock results in a mean-reverting negative (positive) effect on asset prices. The presence of mean reversion from increasing trading frequency occurs globally for all shocks and not just for relatively large shocks, as is the case for the MIC-1 model. Miller, Muthuswamy and Whaley (1994) find that this result holds empirically in the case of stocks. Campbell and Viceira (2005) also report mean reversion in stock returns.

Model MIC-3 in Figure 1 shows that the absence of smart money trading does not qualitatively change the base case in MIC-1 for the chosen parameterization. In contrast, eliminating feedback trading has a significant effect on the qualitative shape of the mean impact...
curve with MIC-4 now exhibiting a positive slope. Here the positive slope arises from the presence of nonsynchronous trading, which causes returns to be positively correlated. This type of model is used by Nelson (1991) to analyze the relationship between risk and return in asset markets. The results of model MIC-4 are also consistent with the empirical results of Campbell and Viceira (2005) who report evidence of mean aversion in the case of real returns on T-bills.

Figure 2 compares the base case model given by MIC-1, to the smart trading model (MIC-5) and feedback trading model (MIC-6), both in the absence of nonsynchronous trading. The parameterizations chosen are:

<table>
<thead>
<tr>
<th>Mean impact curves</th>
<th>Parameters</th>
<th>( \gamma_0 )</th>
<th>( \gamma_1 )</th>
<th>( \lambda_1 )</th>
<th>( \gamma_2 )</th>
<th>( \alpha_0 )</th>
<th>( \alpha_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIC-1</td>
<td>0.1</td>
<td>0.3</td>
<td>-0.1</td>
<td>-0.1</td>
<td>0.1</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>MIC-5</td>
<td>0.1</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.0</td>
<td>0.1</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>MIC-6</td>
<td>0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>-0.1</td>
<td>0.1</td>
<td>0.1</td>
<td></td>
</tr>
</tbody>
</table>

Model MIC-5, yields an inverted U-shaped MIC schedule which is the mirror of the news impact curve presented by Engle and Ng (1993) for the simple ARCH model. This model also corresponds to the GARCH-M class of models investigated by Engle, Lilien and Robins (1987) to study the risk-return relationship. Changing the sign of the parameter \( \lambda \) from a negative value to a positive value has the effect of transforming the MIC schedule to being U-shaped. The MIC-6 model exhibits a similar qualitative MIC schedule to the MIC-2 model in Figure 1, whereby positive feedback trading results in negatively correlated returns.

The alternative types of mean impact curves presented in Figures 1 and 2 show that a range of behavior may occur even for a simple ARCH (1) model given by (33). In general, more involved relationships between the conditional mean and news can be uncovered by specifying more elaborate models of the conditional variance. For example, to allow for longer memory the
Figure 2: Mean impact curves of alternative models (MIC-1, MIC-5, MIC-6), based on the ARCH (1)
conditional variance: MIC-1 is the benchmark model that contains all three trading channels. The equation for the
benchmark model is
\[ \mu_t = \gamma_0 + \lambda \alpha_0 + (\gamma_1 + \gamma_2) \mu_{t-1} + (\gamma_1 + \gamma_2) \epsilon_{t-1} + (\lambda \alpha_0 + \gamma_1 \alpha_1 \mu_{t-1}) \epsilon_{t-1} + \gamma_0 \alpha_0 \epsilon_{t-1} \]
where the term \( \mu_{t-1} \) is the expected return at time \( t \) and \( \epsilon_{t-1} \) is the unpredictable return at time \( t-1 \). The term \( \gamma_0 \) is the risk free rate of return, the parameter \( \lambda \) measures the risk premium. The parameter \( \gamma_1 \) corresponds to nonsynchronous trading, \( \gamma_2 \) represents positive feedback trading. The parameters \( \alpha_0, \alpha_1 \) are in the ARCH (1) variance process. The shape of the
above MIC-1 is indicative of cases with \( \gamma_0 = 0.1, \gamma_1 = 0.3, \lambda = -0.1, \gamma_2 = -0.1 \) and \( \alpha_0 = 0.1, \alpha_1 = 0.1 \). MIC-5 excludes nonsynchronous trading and feedback trading, MIC-6 excludes nonsynchronous trading and smart money trading.

GARCH model of Bollerslev (1986) can be specified. An even more general model that allows for asymmetries in volatility arising from leverage effects (Black (1976)), as in the specification of GJR (1, 1) model developed by Glosten, Jagannathan and Runkle (1993).
The mean impact curve for the GJR (1, 1) specification now becomes

\[
\mu_{s,t} = \begin{cases} 
    a_{z,0}^* + a_{z,1}^* \varepsilon_{s,t-1} + a_{z,2}^* \varepsilon_{s,t-1}^2 + a_{z,3}^* \varepsilon_{s,t-1}^3 : & \varepsilon_{s,t-1} < 0 \\
    a_{z,0}^* + a_{z,1}^* \varepsilon_{s,t-1} + a_{z,2}^* \varepsilon_{s,t-1}^2 + a_{z,3}^* \varepsilon_{s,t-1}^3 : & \varepsilon_{s,t-1} \geq 0 
\end{cases}
\]

where

\[
a_{z,0} = \gamma_0 + \lambda \alpha_0 + (\gamma_1 + \gamma_2 \alpha_0) \mu_{s,t-1} + (\lambda + \gamma_2 \mu_{s,t-1}) \beta \sigma_{s,t-1}^2 \\
a_{z,1} = \gamma_1 + \gamma_2 (\alpha_0 + \beta \sigma_{s,t-1}^2) \\
a_{z,2} = \lambda (\alpha_1 + \varphi) + (\gamma_2 \alpha_1 + \gamma_1 \varphi) \mu_{s,t-1} \\
a_{z,3} = \gamma_2 (\alpha_1 + \varphi)
\]

Figure 3 highlights the effect of increasing memory in the GARCH conditional variance, on the mean impact curve. The parameterizations of the feedback trading model without asymmetry are chosen as:

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Mean impact curves</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0$</td>
<td>$\gamma_1$</td>
</tr>
<tr>
<td>MIC-1</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-7</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-8</td>
<td>0.1</td>
</tr>
</tbody>
</table>

As before, MIC-1 is the benchmark case, where the conditional variance has short memory ($\alpha_1 + \beta_1 = 0.1$) and no asymmetry $\varphi = 0$. Models MIC-7 and MIC-8 exhibit respectively moderate
memory \((\alpha_t + \beta_t = 0.6)\) and longer memory \((\alpha_t + \beta_t = 0.9)\). Figure 3 shows that the effect of increasing memory in the conditional variance is to flatten out the MIC, so the effects of current news on the conditional mean are partially nullified. This can be interpreted as a form of ‘shock’ smoothing where the effects of a shock are spread out over time.

Figure 4 highlights the effect of asymmetry in the conditional variance, on the mean impact curve. The parameterizations of the feedback trading model are chosen as:

<table>
<thead>
<tr>
<th>Mean impact curves</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\gamma_0)</td>
</tr>
<tr>
<td>MIC-1</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-9</td>
<td>0.1</td>
</tr>
<tr>
<td>MIC-10</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Comparing the MIC-9 \((\varphi = 0.05)\) and MIC-10 \((\varphi = 0.1)\) to the benchmark case of no asymmetry \((\varphi = 0)\) shows that increasing asymmetry has the effect of rotating the mean impact curve upwards for negative values of news, with the rotation centered at \(\epsilon_{t+1} = 0\). This model can explain how the conditional mean and the conditional variance can behave differently to shocks. For example, a negative shock of \(\epsilon_{t+1} = -4\), results in a large increase in the conditional variance, but has hardly any effect on the conditional mean for the large memory model MIC-10 reported in Figure-4.
Figure 3: Mean impact curves of alternative models (MIC-1, MIC-7, MIC-8), based on the GJR (1, 1) conditional variance: MIC-1 is the benchmark model that contains all three trading channels where the conditional variance has short memory. The equation for the benchmark model is

\[
\begin{align*}
\mu_{t,t} &= \begin{cases} 
  a_{0,0}^- + a_{0,1}^- \epsilon_{t-1} + a_{1,2}^- \epsilon_{t-1}^{*2} + a_{2,3}^- \epsilon_{t-1}^{*3}, & \epsilon_{t-1} < 0 \\
  a_{0,0}^+ + a_{0,1}^+ \epsilon_{t-1} + a_{1,2}^+ \epsilon_{t-1}^{*2} + a_{2,3}^+ \epsilon_{t-1}^{*3}, & \epsilon_{t-1} \geq 0
\end{cases}
\end{align*}
\]

where \( a_{i,j}^- = \gamma_i + \lambda \alpha_i + (\gamma_i + \gamma a_i) \mu_{t-1} + (\lambda + \gamma \mu_{t-1}) \beta_i \sigma_{t-1} \). The term \( \mu_{i,j} \) is the expected return at time \( t \) and \( \epsilon_{t-1} \) is the unpredictable return at time \( t-1 \). The term \( a_{i,j}^- = \gamma_i + \gamma a_i (\alpha_i + \beta_i \sigma_{t-1}) \), where the parameter \( \gamma_i \) corresponds to nonsynchronous trading, \( \gamma \) represents positive feedback trading. The parameter \( \gamma_6 \) measures the risk free rates of return. The term \( a_{i,j}^- = \lambda (\alpha_i + \varphi) + (\gamma_i + \gamma a_i) \mu_{t-1} + (\lambda + \gamma \mu_{t-1}) \beta_i \sigma_{t-1} \), where \( \lambda \) measures the risk premium. The parameters \( \alpha_i, \alpha_i, \text{ and } \beta_i \) are in the GJR (1, 1) variance process. The term \( a_{i,j}^- = \gamma_i (\alpha_i + \varphi) \) and \( a_{i,j}^- = \gamma a_i \), where \( \varphi \) captures the leverage effect. The shape of the above MIC-1 is indicative of cases with \( \gamma_0 = 0.1, \gamma_1 = 0.3, \lambda = -0.1, \gamma_2 = -0.1, \alpha_0 = 0.1, \text{ and } \alpha_1 + \beta_i = 0.1 \). MIC-7 allows for moderate memory \( \alpha_i + \beta_i = 0.6 \) in the conditional variance. MIC-8 allows for longer memory \( \alpha_i + \beta_i = 0.9 \) in the conditional variance.
Figure 4: Mean impact curves of alternative models (MIC-1, MIC-9, MIC-10), based on the GJR (1, 1) conditional variance: MIC-1 is the benchmark model that contains all three trading channels where the conditional variance has short memory. The equation for the benchmark model is

\[
\mu_{t,t} = \begin{cases} 
    a^{-}_{t,0} + a^{-}_{t,1} \varepsilon_{t,t-1} + a^{-}_{t,2} \varepsilon_{t,t-1}^2 + a^{-}_{t,3} \varepsilon_{t,t-1}^3, & \varepsilon_{t,t-1} < 0 \\
    a^{+}_{t,0} + a^{+}_{t,1} \varepsilon_{t,t-1} + a^{+}_{t,2} \varepsilon_{t,t-1}^2 + a^{+}_{t,3} \varepsilon_{t,t-1}^3, & \varepsilon_{t,t-1} \geq 0
\end{cases}
\]

where \( a^{-}_{t,0} = a^{+}_{t,0} = \gamma_0 + \lambda \alpha_0 + (\gamma_1 + \gamma_2 \alpha_0) \mu_{t,t-1} + (\lambda + \gamma_1 \mu_{t,t-1}) \beta \sigma_{t,t-1}^2 \). The term \( \mu_{t,t} \) is the expected return at time \( t \) and \( \varepsilon_{t,t-1} \) is the unpredictable return at time \( t-1 \). The term \( a^{-}_{t,1} = a^{+}_{t,1} = \gamma_1 + \gamma_2 (\alpha_1 + \beta_1 \sigma_{t,t-1}^2) \) where the parameter \( \gamma_1 \) corresponds to nonsynchronous trading, \( \gamma_2 \) represents positive feedback trading. The parameter \( \gamma_0 \) measures the risk free rates of return. The term \( a^{-}_{t,2} = a^{+}_{t,2} = \gamma_1 + \gamma_2 (\alpha_2 + \beta_2 \sigma_{t,t-1}^2) \) where \( \lambda \) measures the risk premium. The parameters \( \alpha_0, \alpha_1 \) and \( \beta_1 \) are in the GJR (1, 1) variance process. The term \( a^{-}_{t,3} = a^{+}_{t,3} = \gamma_3 \alpha_3 \) and \( a^{-}_{t,3} = a^{+}_{t,3} = \gamma_3 \alpha_3 \) where \( \varphi \) captures the leverage effect. The shape of the above MIC-1 is indicative of cases with \( \gamma_0 = 0.1, \gamma_1 = 0.3, \lambda = -0.1, \gamma_2 = -0.1, \alpha_0 = 0.1, \) and \( \alpha_1 + \beta_1 = 0.1 \). MIC-9 allows for moderate memory \( \alpha_1 + \beta_1 = 0.6 \) in the conditional variance and \( \varphi = 0.05 \). MIC-10 allows for longer memory \( \alpha_1 + \beta_1 = 0.9 \) in the conditional variance and \( \varphi = 0.1 \).
4.2 Testing the mean impact curve

In this section Lagrange multiplier (LM) test statistics are derived to test the mean impact curve under alternative scenarios. These test statistics represent analogies of the statistics derived by Engle and Ng (1993) to test the news impact curve. Whilst the form of the tests are motivated from the feedback trading model, the tests can also be interpreted in a more nonparametric way which can be applied nonetheless without specifying a parametric model of either the mean or the variance.

In deriving the test statistics, three versions are presented. The first test is referred to as the “inefficient” test, which is easily constructed by estimating two least squares regression equations. The second test is referred to as the “efficient” test, which is slightly more involved than the inefficient version as the second stage regression equation requires estimation by weighted least squares where the weights are obtained by estimating a conditional variance model by an iterative maximum likelihood procedure. The inefficient version of the test whilst simple to compute, has the potential disadvantage is that it may have size properties that are not necessarily well approximated by asymptotic theory in finite samples. To circumvent this problem while still maintaining a test that is relatively easy to implement, a third version of the MIC test is proposed whereby the weights are computed by estimating a variance regression equation by least squares. This test is referred to as the “White” version of the MIC test (see White (1980)). The MIC tests consist of testing the parameters \( \gamma_0, \gamma_1, \lambda \) and \( \gamma_2 \) in the conditional mean Equation (32).

\[
\gamma_1 = \lambda = \gamma_2 = 0, \quad (41)
\]
For the joint restriction the conditional mean under the null hypothesis reduces to $\mu_{t,i} = \gamma_0$, in which case the conditional mean exhibits no structure. Tests based on individual restrictions constitute tests of particular aspects of the feedback trading model. For example, a test that $\gamma_1 = 0$ represents a test that there is no nonsynchronous trading, a test based on the restriction $\lambda = 0$ is a test of no smart money trading, whereas a test of $\gamma_2 = 0$ corresponds to a test of no feedback trading.

To derive the mean impact curve diagnostic tests, assume that the disturbance term in (10) is normally distributed\textsuperscript{12}

$$e_{t,i} \sim N(0, \sigma_{t,i}^2)$$ (42)

For a sample of $t = 1, 2, L, T$ observations, the normal log-likelihood is

$$\ln L = -\frac{T}{2} \ln 2\pi - \frac{1}{2} \sum_{t} \ln \sigma_{t,i}^2 - \frac{1}{2} \sum_{t} \frac{(R_{t,i} - \mu_{t,i})^2}{\sigma_{t,i}^2},$$ (43)

where $\mu_{t,i}$ is given by (32) and $\sigma_{t,i}^2$ is the conditional volatility. In deriving the mean impact curve statistics, the volatility model is specified initially as

$$\sigma_{t,i}^2 = \alpha_0 + \alpha_1 R_{t,i-1}^2$$ (44)

\textsuperscript{12} An alternative strategy is to replace the assumption of normality with a nonnormal distribution. One approach would be to use the approach of Andreev, Kanto and Malo (2007) to choose a distribution of stock returns within the Pearson family of distributions.
Generalizing the MIC test statistics to allow for more general volatility structures as given by ARCH (1) or GJR (1, 1) are discussed below. The first order derivatives with respect to the conditional mean parameters are

\[
\frac{\partial \ln L}{\partial \gamma_0} = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}} \left( \frac{\partial \mu_{st}}{\partial \gamma_0} \right) = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}}
\]

\[
\frac{\partial \ln L}{\partial \gamma_1} = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}} \left( \frac{\partial \mu_{st}}{\partial \gamma_1} \right) = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}} R_{s,t-1}
\]

\[
\frac{\partial \ln L}{\partial \lambda} = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}} (\alpha_0 + \alpha_1 R_{s,t-1}^2)
\]

\[
\frac{\partial \ln L}{\partial \gamma_2} = \sum_{t=1}^T \frac{R_{st} - \mu_{st}}{\sigma_{st}} (\alpha_0 + \alpha_1 R_{s,t-1}^2) R_{s,t-1},
\]

while the first order conditions with respect to the conditional variance parameters are

\[
\frac{\partial \ln L}{\partial \alpha_0} = \sum_{t=1}^T \left( -\frac{1}{2\sigma_{st}^2} + \frac{(R_{st} - \mu_{st})^2}{2\sigma_{st}^2} \right) \frac{\partial \sigma_{st}^2}{\partial \alpha_0} = \sum_{t=1}^T \left( -\frac{1}{2\sigma_{st}^2} + \frac{(R_{st} - \mu_{st})^2}{2\sigma_{st}^2} \right)
\]

\[
\frac{\partial \ln L}{\partial \alpha_1} = \sum_{t=1}^T \left( -\frac{1}{2\sigma_{st}^2} + \frac{(R_{st} - \mu_{st})^2}{2\sigma_{st}^2} \right) \frac{\partial \sigma_{st}^2}{\partial \alpha_1} = \sum_{t=1}^T \left( -\frac{1}{2\sigma_{st}^2} + \frac{(R_{st} - \mu_{st})^2}{2\sigma_{st}^2} \right) R_{s,t-1}^2.
\]

Evaluating the derivatives under the joint restrictions in (41) and rearranging gives

\[
\frac{\partial \ln L}{\partial \gamma_0} \bigg|_{H_0} = \sum_{t=1}^T \left( \frac{R_{st} - \gamma_0}{\sigma_{st}} \right) \frac{1}{\sigma_{st}}
\]

\[
\frac{\partial \ln L}{\partial \gamma_1} \bigg|_{H_0} = \sum_{t=1}^T \left( \frac{R_{st} - \gamma_0}{\sigma_{st}} \right) \frac{R_{s,t-1}}{\sigma_{s,t}}
\]
This suggests that an LM test of the joint restrictions is given by first estimating the constrained model

\[ R_{s,t} = \gamma_0 + \varepsilon_{s,t}, \]

\[ \varepsilon_{s,t} \sim N\left(0, \sigma_{s,t}^2\right) \]

\[ \sigma_{s,t}^2 = \sigma_0 + \alpha_0 R_{s,t-1}^2, \quad \text{(45)} \]

by maximum likelihood to compute \( \gamma_0, \alpha_0, \alpha_1 \) and hence \( \sigma_{s,t}^2 \). The test statistic is constructed by estimating the weighted regression equation in the second step

\[ \frac{R_{s,t}}{\sigma_{s,t}} = \frac{\phi_{0}}{\sigma_{s,t}} + \phi_{1} \frac{R_{s,t-1}}{\sigma_{s,t}} + \phi_{2} \frac{R_{s,t-1}^2}{\sigma_{s,t}} + \phi_{3} \frac{R_{s,t-1}^3}{\sigma_{s,t}} + \eta_{s,t}, \quad \text{(46)} \]

where \( \eta_{s,t} \) is a disturbance term, while the parameters \( \gamma_0, \alpha_0, \alpha_1 \) and conditional variance \( \sigma_{s,t}^2 \) are replaced by the constrained maximum likelihood estimates from the first step. An overall test
of the restrictions is given by

\[ LM = T R^2 \]  

(47)

where \( T \) is the sample size, \( R^2 \) is the coefficient of determination from the second stage regression. The LM statistic is distributed asymptotically under the null hypothesis as \( \chi^2_3 \), i.e., LM test statistic follows a chi-square \( (\chi^2) \) distribution with three degrees of freedom. This version of the LM test is referred to as the efficient version of the MIC test as it uses an efficient estimator in the second stage when constructing (47). Alternatively, an F-test can be employed to test the joint restrictions, while tests of individual models can also be carried out using a \( t \)-test on the parameters \( \phi_i \) in (46).

The above testing procedure requires specifying and estimating a conditional variance model. As the conditional variance is used in the estimation as a weighting procedure that yields efficient parameter estimates, an alternative approach is to perform the test without any weights. Thus the inefficient form of the MIC test is simply to estimate the following regression equation

\[ R_{x,t} = \phi_0 + \phi_1 R_{x,t-1} + \phi_2 R_{x,t-2}^2 + \phi_3 R_{x,t-1}^3 + \eta_{x,t} \]  

(48)

and compute the statistic in (47) which is distributed asymptotically under the null hypothesis as \( \chi^2_3 \). As before, individual tests can also be performed on separate models\(^{13}\). This form of the test statistic has the convenience of not having to specify the conditional variance model and is relatively more simple to compute as it does not require an iterative algorithm to estimate the

\(^{13}\) The construction of this form of the MIC test is equivalent to the Lagrange multiplier test of STAR models proposed by Luukkonen, Saikkonen and Terasvirta (1988), where under the null hypothesis of no nonlinearity expected returns are equal to a constant (see also van Dijk, Terasvirta and Franses (2002)).
conditional variance to be used in the second stage of the test. The disadvantage is that this statistic may not be correctly sized and may exhibit some loss of power in finite samples as a result of the parameters not being estimated efficiently.

An intermediate approach between the efficient and inefficient versions of the MIC test that has the convenience of the inefficient test of being easy to compute while potentially having better sampling properties comparable to the efficient version of the MIC test, is to approximate the conditional variance using the same regressors in the mean equation. Formally the steps are as follows. First, compute the demeaned returns

\[ e_{t,i} = R_{t,i} - \bar{R}_i. \]  

(49)

Second, estimate the regression equation

\[ \ln e_{t,i} = \delta_0 + \delta_1 R_{t,i-1} + \delta_2 R_{t,i-1}^2 + \delta_3 R_{t,i-1}^3 + u_{t,i}, \]  

(50)

where \( u_{t,i} \) is a disturbance term and let the predicted values of this estimated equation be the estimates of the conditional variance, \( \sigma_{t,i}^2 \). Third, the weighted regression equation in (46) is estimated with \( \sigma_{t,i}^2 \) replaced by the estimate from the previous step, namely \( \hat{\sigma}_{t,i}^2 = \exp(\delta_0 + \delta_1 R_{t,i-1} + \delta_2 R_{t,i-1}^2 + \delta_3 R_{t,i-1}^3) \) with all parameters replaced by their maximum likelihood estimates\(^{14}\). The statistic in (47) is then computed as before. As the variance equation in (50) is equivalent to performing a White test of heteroskedasticity, this version of the MIC test is

\(^{14}\) The logarithmic form of the conditional variance equation is chosen to ensure that the conditional variance is positive for all \( t \). Technically, given the assumption of normality, one half of the residual variance could be added to the exponent of the mean equation to correct for Jensen’s inequality.
referred to as the White adjusted version (see White (1980)). This test has the advantage of simplicity compared to the efficient version of the MIC test as computation of the test statistic just requires performing two least squares regressions.

To highlight the size and power properties of the three MIC tests, the following Monte Carlo experiments are conducted. The data generating process (DGP) of the experiments is

\[
R_{t,i} = \gamma_0 + \lambda \sigma_{i,t}^\gamma + (\gamma_1 + \gamma_2 \sigma_{i,t}^\gamma) R_{t,i-1} + \epsilon_{i,t},
\]

\[
\epsilon_{i,t} \sim N(0, \sigma_{i,t}^\gamma)
\]

\[
\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \epsilon_{i,t-1}^2 + \varphi S_{t,i-1} \epsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2
\]

The following parameterizations are used to compute the size of the tests:

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Parameters</th>
<th>(\gamma_0)</th>
<th>(\gamma_1)</th>
<th>(\lambda)</th>
<th>(\gamma_2)</th>
<th>(\alpha_0)</th>
<th>(\alpha_1)</th>
<th>(\beta_1)</th>
<th>(\varphi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.1)</td>
<td>(0.1)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.1)</td>
<td>(0.1)</td>
<td>(0.8)</td>
<td>(0.0)</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.0)</td>
<td>(0.1)</td>
<td>(0.1)</td>
<td>(0.8)</td>
<td>(0.1)</td>
<td></td>
</tr>
</tbody>
</table>

Under the null hypothesis the mean impact curve exhibits no structure with a population value of zero. Experiment A represents an ARCH (1) model with short memory \((\alpha_1 + \beta_1 = 0.1)\), Experiment B is based on a GARCH (1, 1) model with longer memory \((\alpha_1 + \beta_1 = 0.9)\), while Experiment C uses a GJR model with an asymmetric conditional variance. In constructing the efficient version of the MIC test the constrained model is estimated by maximum likelihood, with the estimated conditional variance chosen to match the DGP specification of the conditional variance.
variance in each experiment. In constructing the White adjusted version of the test the same model as that given in (50), is used to estimate the conditional variance in each experiment. The empirical size of the inefficient and efficient MIC joint tests, together with the White adjusted version, are given in Table 1 using the 1%, 5% and 10% critical values from a $\chi^2$ distribution with 3 degrees of freedom. The Monte Carlo experiments are based on simulating the model with a sample of size $T = 1750$, with the number of replications set at 10,000. This choice of the sample size is dictated by the number of observations used in the empirical application.

Table 1 shows that the inefficient version of the joint test is over-sized, with all rejection probabilities in excess of their nominal values. The extent of this test being over-sized becomes progressively worse as the memory of the conditional variance increases (Model B) and the conditional variance exhibits asymmetries (Model C). For example, the empirical size of the inefficient test in Experiment A is 13.020%, which increases to 19.510% for Experiment B and 43.550% for Experiment C, compared to a nominal size of 5%. In contrast, the efficient version of the joint MIC test is correctly sized for all three experiments conducted. In addition, the White adjusted version of the MIC test is also correctly sized for all three experiments, suggesting that the general variance structure adopted in Equation (50) serves as a good approximation to the true conditional variance.

---

15 A number of tolerances is imposed on the maximum likelihood procedure. When the tolerance is not satisfied, a new set of random numbers is generated. The percentage number of times the algorithm fails is less than 1% for all experiments.
Table 1

Monte Carlo experiments of type one. Experiments are performed to check the size of the MIC tests based on the data generating process given below

\[ R_{i,t} = \gamma_0 + \lambda \sigma_{i,t}^\gamma + (\gamma_2 + \gamma_2 \sigma_{i,t-1}^\gamma) R_{i,t-1} + \epsilon_{i,t} \]
\[ \epsilon_{i,t} \sim N(0, \sigma_{i,t}^\gamma) \]
\[ \sigma_{i,t}^\gamma = \alpha_0 + \alpha_1 \epsilon_{i,t-1}^\gamma + \phi S_{i,t-1} \epsilon_{i,t-1}^\gamma + \beta_1 R_{i,t-1}^\gamma \]

The term \( R_{i,t} \) is the simulated return at time \( t \) and \( \epsilon_{i,t} \) is the unpredictable return at time \( t \). Conditional variance \( \sigma_{i,t}^\gamma \) follows the GJR (1, 1) process where \( \phi \) captures the leverage effect. In constructing the White adjusted version of the test \( \epsilon_{i,t}^\gamma = \exp(\delta_t + \delta_1 R_{i,t-1} + \delta_2 R_{i,t-1} + \delta_3 \epsilon_{i,t-1}^\gamma) \) is used to estimate variance. The simulated empirical size (percentage) of the MIC joint tests is based on a sample size of \( T = 1750 \) and 10,000 replications. Experiment A is based on the parameterizations of \( \gamma_0 = 0.0, \gamma_1 = 0.0, \lambda = 0.0, \gamma_2 = 0.0, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta_1 = 0.0 \) and \( \phi = 0.0 \).

Experiment B is based on the parameterizations of \( \gamma_0 = 0.0, \gamma_1 = 0.0, \lambda = 0.0, \gamma_2 = 0.0, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta_1 = 0.8 \) and \( \phi = 0.0 \). Experiment C is based on the parameterizations of \( \gamma_0 = 0.0, \gamma_1 = 0.0, \lambda = 0.0, \gamma_2 = 0.0, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta_1 = 0.8 \) and \( \phi = 0.1 \).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Inefficient</th>
<th>Efficient</th>
<th>White Adjusted Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1% 5% 10%</td>
<td>1% 5% 10%</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>28.770 43.550 52.530 1.020 5.040 10.180 1.510 5.840 10.310</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 2

Monte Carlo experiments of type two. Experiments are performed to check the size of the MIC tests based on the data generating process given below

\[ R_{t,j} = \gamma_0 + \lambda \sigma^2_{j,t} + (\gamma_1 + \gamma_2 \sigma^2_{j,t})R_{j,t-1} + \epsilon_{t,j} \]
\[ \epsilon_{t,j} \sim N(0, \sigma^2_{t,j}) \]
\[ \sigma^2_{j,t} = \alpha_0 + \alpha_1 \epsilon^2_{j,t-1} + \varphi S_{t,j-1} \epsilon^2_{j,t-1} + \beta \sigma^2_{t,j-1} \]

The term \( R_{t,j} \) is the simulated return at time \( t \) and \( \epsilon_{t,j} \) is the unpredictable return at time \( t \). Conditional variance \( \sigma^2_{j,t} \) follows the GJR (1, 1) process where \( \varphi \) captures the leverage effect. In constructing the White adjusted version of the test \( \epsilon_{t,j}^* = \exp(\delta_0 + \delta_1 R_{j,t-1} + \delta_2 R^2_{j,t-1} + \delta_3 R^3_{j,t-1}) \) is used to estimate variance. Simulated empirical size (percentage) of the MIC joint tests is based on a sample size of \( T = 1750 \) and 10,000 replications. Experiment D is based on the parameterizations of \( \gamma_0 = 0.2, \gamma_1 = 0.1, \lambda = -0.01, \gamma_2 = -0.001, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta = 0.0 \) and \( \varphi = 0.0 \). Experiment E is based on the parameterizations of \( \gamma_0 = 0.2, \gamma_1 = 0.1, \lambda = -0.01, \gamma_2 = -0.001, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta = 0.8 \) and \( \varphi = 0.0 \). Experiment F is based on the parameterizations of \( \gamma_0 = 0.2, \gamma_1 = 0.1, \lambda = -0.01, \gamma_2 = -0.001, \alpha_0 = 0.1, \alpha_1 = 0.1, \beta = 0.8 \) and \( \varphi = 0.1 \).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Inefficient 1%</th>
<th>Inefficient 5%</th>
<th>Inefficient 10%</th>
<th>Efficient 1%</th>
<th>Efficient 5%</th>
<th>Efficient 10%</th>
<th>White Adjusted Test 1%</th>
<th>White Adjusted Test 5%</th>
<th>White Adjusted Test 10%</th>
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<tbody>
<tr>
<td>D</td>
<td>67.930</td>
<td>86.580</td>
<td>92.870</td>
<td>85.910</td>
<td>95.990</td>
<td>98.010</td>
<td>51.350</td>
<td>71.340</td>
<td>80.330</td>
</tr>
<tr>
<td>E</td>
<td>47.290</td>
<td>76.670</td>
<td>86.980</td>
<td>80.290</td>
<td>93.230</td>
<td>96.060</td>
<td>67.850</td>
<td>86.420</td>
<td>92.110</td>
</tr>
<tr>
<td>F</td>
<td>4.670</td>
<td>30.620</td>
<td>54.440</td>
<td>84.950</td>
<td>94.650</td>
<td>96.920</td>
<td>64.790</td>
<td>84.750</td>
<td>91.750</td>
</tr>
</tbody>
</table>
The empirical size results suggest that in applying the inefficient version of the MIC test, this test incorrectly finds evidence of nonlinear mean impact curve more often that it should when the conditional volatility exhibits strong memory and asymmetries. The results of the efficient and White adjusted versions of the joint MIC test suggest that the asymptotic critical values represent a good approximation to the finite sample distribution for a sample of size $T = 1750$.

The empirical power properties of the MIC joint tests are presented in Table 2 for three experiments. The experiments are based on the following parameterizations:

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0$</td>
<td>$\gamma_1$</td>
</tr>
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<td>D</td>
<td>0.2</td>
</tr>
<tr>
<td>E</td>
<td>0.2</td>
</tr>
<tr>
<td>F</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The powers are size-adjusted by using the 1%, 5% and 10% empirical critical values computed from the respective experiments in Table 1.

Table 2 shows that the efficient and White adjusted versions of the joint MIC test display good and similar power properties. Both power functions progressively increase as the memory of the conditional variance increases and as the strength of the asymmetry in the conditional variance increases. Again these results highlight the ability of the White adjusted version of the MIC joint test to provide an excellent approximation to the underlying conditional variance that is simply estimated by least squares. The opposite result occurs for the inefficient version of the MIC test whereby its power diminishes as the complexity of the conditional variance increases.
Chapter 5
The data

This chapter consists of two parts. The information on data sets is described in Part 5.1 and Part 5.2 describes the preliminary diagnostics of stock returns.

5.1 Information on data sets

In this section the mean impact curve framework developed in the previous chapter is used to uncover potential nonlinear structures in daily returns in the Helsinki Stock Exchange index (HEX) and eight industry-sorted portfolio components of this index (Bank & Finance, Other Service, Metal & Engineering, Forest, Other Industry, Telecom & Electronics, Trade and Food). The Finnish stock exchange is small both in terms of overall capitalization and in terms of the number of companies listed in the main stock exchange, the HEX. Consequently, the market is generally more volatile compared to many other European equity markets.¹⁶


Figure 5: Time series plot of all price series. The daily price series are obtained from the Helsinki Stock Exchange for the period 2nd January 1997 to 30th December 2003. Panel 1 represents the daily prices of the Bank and Finance Industry, Panel 2 represents the daily prices for the Other Service Industry, Panel 3 represents the daily prices for the Metal and Engineering Industry, Panel 4 represents the daily prices for the Forest Industry, Panel 5 represents the daily prices for the Other Industry, Panel 6 represents the daily prices for the Telecom and Electronics Industry, Panel 7 represents the daily prices for the Trade Industry, Panel 8 represents the daily prices for the Food Industry and Panel 9 represents the daily prices for overall HEX index.
Figure 6: Time series plot of all return series. The returns are logarithmic returns measured in percentage (multiplied by 100). The sample period is from 2nd January 1997 to 30th December 2003. Panel 1 represents the daily logarithmic returns of the Bank and Finance Industry, Panel 2 represents the daily logarithmic returns for the Other Service Industry, Panel 3 represents the daily logarithmic returns for the Metal and Engineering Industry, Panel 4 represents the daily logarithmic returns for the Forest Industry, Panel 5 represents the daily logarithmic returns for the Other Industry, Panel 6 represents the daily logarithmic returns for the Telecom and Electronics Industry, Panel 7 represents the daily logarithmic returns for the Trade Industry, Panel 8 represents the daily logarithmic returns for the Food Industry and Panel 9 represents the daily returns for overall HEX index.
show that the volatilities play an important role in the change of the level of correlation in Finnish stock returns. The price indices begin 2nd January 1997 and end 30th December 2003, a total of 1745 observations. The nine price indices are presented in Figure 5. The HEX index together with Bank & Finance, Other Service and Telecom & Electronics, show the effects of dot-com with sharp rises in all indices until 2000, followed by large falls in the indices during 2000, with this negative trend continuing for the next three years. For some indices (Trade and Other Industry) the trend is positive in the latter part of the sample while some other indices exhibit very little trend (Forest, Metal & Engineering and Food) over the same period.

Returns are computed as the differences of the natural logarithms of the price indices and multiplied by 100 to express the returns as a percentage. This yields an effective sample size of \( T = 1744 \) observations. The daily returns are plotted in Figure 6. Inspection of these plots shows that volatility is not constant. These plots also highlight the magnitude of the bursting of the dot-com bubble with the largest observed daily fall in returns on the HEX being in excess of 15%, while Other Service and Telecom & Electronics recorded daily falls in excess of 20% at the time.

5.2 Preliminary diagnostics

Descriptive statistics of the nine returns series are reported in Table 3. Telecom and Electronics has the highest average return over the sample period with a mean of 0.085\( \times 252 = 21.42\% \) per annum, while Metal & Engineering and Trade have the lowest average return with a sample mean of 0.012 \( \times 252 = 3.024\% \) per annum. Associated with Telecom & Electronics having the high average return, this stock also has the highest variability with a standard deviation of 3.149 compared to 1.226 for Metal & Engineering and 1.056 for Trade. The Sharp ratio, computed here
This table presents the summary statistics of daily stock returns from the Helsinki Stock Exchange for the period 2nd January 1997 to 30th December 2003. The returns are logarithmic returns measured in percentage (multiplied by 100). The AR (1) coefficient on logarithmic returns which measures the degree of nonsynchronous trading (see Nelson (1991)), reported in this table. The statistic skewness is the coefficient of skewness and the statistic kurtosis (Excess) is the coefficient of excess kurtosis of logarithmic returns. For a standard normal variable, the value of the coefficient of skewness and the value of the coefficient of kurtosis (Excess) are zero. P-value of the skewness and P-value of the kurtosis (Excess) are estimated by bootstrap statistical technique. Ljung-Box (n) is the Ljung-Box (LB) test statistics for n\textsuperscript{th} order autocorrelation of logarithmic returns.

<table>
<thead>
<tr>
<th>Sample Statistics</th>
<th>Industry-sorted Portfolios and The HEX index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bank Finance</td>
</tr>
<tr>
<td>Sample mean</td>
<td>0.049</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.924</td>
</tr>
<tr>
<td>Sharp ratio</td>
<td>0.025</td>
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<tr>
<td>Skewness</td>
<td>0.116</td>
</tr>
<tr>
<td>P-value of skewness</td>
<td>[0.482]</td>
</tr>
<tr>
<td>Kurtosis (Excess)</td>
<td>2.419</td>
</tr>
<tr>
<td>P-value of kurtosis (Excess)</td>
<td>[0.000]</td>
</tr>
<tr>
<td>AR (1) coefficient</td>
<td>0.010</td>
</tr>
<tr>
<td>P-value of AR (1) coefficient</td>
<td>[0.664]</td>
</tr>
<tr>
<td>LB(5) for levels</td>
<td>12.809</td>
</tr>
<tr>
<td>P-value of LB(5) for levels</td>
<td>[0.025]</td>
</tr>
<tr>
<td>LB(10) for levels</td>
<td>17.103</td>
</tr>
<tr>
<td>P-value of LB(10) for levels</td>
<td>[0.072]</td>
</tr>
</tbody>
</table>
as the ratio of the mean to the standard deviation, nonetheless suggests that Telecom & Electronics is the better investment of these three stocks from an average return per unit of risk point of view. In fact, the stock referred to as Other Industries, exhibits the best return by this measure with a maximum value of the Sharp ratio of 0.036.

None of the returns display any significant skewness, whereas all returns exhibit significant kurtosis. The test for first order autocorrelation shows strong evidence of a positive autocorrelation at the 5% level in HEX, Other Service, Metal & Engineering and Forest, whilst Trade shows evidence of significant negative autocorrelation. Tests of higher autocorrelation using the Ljung-Box test with 5 lags (LB (5)) and 10 lags (LB (10)) also reveal evidence of autocorrelation in Bank Finance (at the 5% level) and Food (at the 10% level). Other Industry and Telecom and Electronics reveal no evidence of autocorrelation, suggesting that the MIC tests will not be able to detect any evidence of nonlinearities in the returns of these two portfolios.

The linear dependencies described above, may be some form of evidence against the random walk hypothesis. For random walk theory, sets of share price changes are tested for linear independence. Linear independence means that the probability distribution for the price changes during time period $t$ is independent of the sequence of price changes during the previous time period. ADF (Augmented Dickey-Fuller), PP (Phillips and Perron), ARIMA (Autoregressive Integrated Moving Average) models are used in this research, to test for dependence in the series of successive price changes.

ADF tests are implemented in the log price series of all indices to test the randomness of the price series. The regression equation of the version of ADF test with trend can be written as,

$$\Delta \ln \left( P_{s,t} \right) = a_0 + \phi \ln \left( P_{s,t-1} \right) + \theta_0 t + \theta_1 \Delta \ln \left( P_{s,t-1} \right) + \epsilon_{s,t}$$  \hspace{1cm} (54)
where $\Delta \ln (P_{s,t}) = \ln (P_{s,t}) - \ln (P_{s,t-1})$, $P_{s,t}$ represents the prices of security $s$ at time $t$. The variable $t$ represents the trend. The Dickey-Fuller regression can also be written without a trend. The regression equation can be written as,

$$\Delta \ln (P_{s,t}) = a_0 + \phi \ln (P_{s,t-1}) + \theta_1 \Delta \ln (P_{s,t-1}) + \epsilon_{s,t}$$  \hspace{1cm} (55)

However, the ADF test assumes that innovations $\epsilon_{s,t}$ should be distributed homogeneously. Independence and homoskedasticity, however, are rather strong assumptions to make about in empirical financial economic work. Thus an alternative unit root procedure PP test by Phillips (1987) and Phillips and Perron (1988) is used in this research. This test involves the OLS (ordinary least square) regression with trend $t$

$$\ln (P_{s,t}) = a_0 + \theta_0 \left( t - \frac{T}{2} \right) + \phi \ln (P_{s,t-1}) + \epsilon_{s,t}$$ \hspace{1cm} (56)

where $P_{s,t}$ represents the price of today and $T$ denotes the sample size. The PP regression can also be written without a trend. The regression equation can be written as,

$$\ln (P_{s,t}) = a_0 + \phi \ln (P_{s,t-1}) + \epsilon_{s,t}$$ \hspace{1cm} (57)

Under the null hypothesis the critical values of the PP model with a trend and without a trend have the same distribution as the ADF model. If security prices follow the random walk model then $\ln (P_{s,t})$ series should be in a non-stationary situation. That means that the coefficient of $\ln (P_{s,t-1})$, $\phi$ is in fact close to 1. In financial economics, a time series that has a unit root is known as the random walk hypothesis. On the other hand, if the security price indices follow the random walk hypothesis then the appropriate ARIMA model should be ARIMA $(0, 1, 0)$. 
The Wald-Wolfowitz Runs test is also applied to test for the randomness of the price series. A Runs testing is a strong test for randomness in share price movements. It compares the expected number of runs from a random process with the observed number of runs. The test is non-parametric and is independent of the normality assumption and constant variance of data. The number of runs is computed as a sequence of the price changes of the same sign, such as $(++,--,00)$. When the expected number of runs is significantly different from the observed number of runs, the test rejects the null hypothesis that the daily prices are random.

Gujarati (1988) mentions that if in an application it is found that the number of runs is equal to or less than 9 or equal to or greater than 20, one can reject (at the 5% level of significance) the hypothesis that the observed sequence is random. A Runs test converts the total number of runs into $z$ statistic. For large samples the $z$ statistics give the probability of difference between the actual and expected number of runs. The $z$ value greater than or equal to $\pm 1.96$, rejects the null hypothesis of randomness at 5% level of significance (Sharma and Kennedy (1977)). The critical values of $\tau$ for ADF (without trend model) test statistics at the 1%, 5% and 10% levels are -3.44, -2.87 and -2.57 respectively. When a time trend is included the critical values of $\tau$ at the same significant levels are -3.96, -3.41 and -3.12. Table 4 reports that estimated $\tau$ values in every series are below than the ADF (no trend model) critical value -3.44 and ADF (trend model) critical value -3.96 at the 1% level. This evidence is also true for PP test.

Thus, at the 1% level both the ADF and PP test suggest that the stock prices follow the random walk hypothesis. The random walk also implies that the return of security $s$ at time $t$, $R_{ts}$ are not autocorrelated and their probability function is constant through time. As a result, the log price index $\ln(p_{ts})$ of security $s$ at date $t$, should follow ARIMA (0, 1, 0) model. Stock prices do
This table reports random walk hypothesis tests of daily stock prices. The unit root test statistics of stock prices estimated by the Augmented Dickey-Fuller (ADF) test and the Phillips and Perron (PP) test are reported in this table. The data are obtained from the Helsinki Stock Exchange for the period of 2nd January 1997 to 30th December 2003. The critical values of $\tau$ for ADF test (without trend model) and PP test (without trend model) statistics at the 1%, 5% and 10% levels are -3.44, -2.87 and -2.57 respectively. When a time trend is included the critical values of $\tau$ at the same significant levels are -3.96, -3.410 and -3.12. If the estimated $\tau$ value is below the critical $\tau$ value, accept the null: logarithmic price series are non-stationary. ARIMA and a non-parametric Runs test are also reported in this table to examine the randomness of stock prices. The Runs test converts the total number of runs into the $z$ statistics. The $z$ value is greater than or equal to ±1.96, rejects the null hypothesis of randomness at 5% level of significance.

<table>
<thead>
<tr>
<th>Industry-sorted Portfolios and The HEX index</th>
<th>Bank</th>
<th>Finance</th>
<th>Other Service</th>
<th>Metal &amp; Engineering</th>
<th>Forest</th>
<th>Other Industry</th>
<th>Telecom &amp; Electronics</th>
<th>Trade</th>
<th>Food</th>
<th>HEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF test static without trend</td>
<td>-2.980</td>
<td>-2.200</td>
<td>-1.903</td>
<td>-2.892</td>
<td>-0.854</td>
<td>-2.118</td>
<td>-1.290</td>
<td>-1.987</td>
<td>-2.004</td>
<td></td>
</tr>
<tr>
<td>ADF test static with trend</td>
<td>-2.664</td>
<td>-2.185</td>
<td>-1.819</td>
<td>-3.072</td>
<td>-1.457</td>
<td>-1.292</td>
<td>-1.208</td>
<td>-2.198</td>
<td>-1.467</td>
<td></td>
</tr>
<tr>
<td>PP test static without trend</td>
<td>-3.017</td>
<td>-2.166</td>
<td>-1.786</td>
<td>-2.865</td>
<td>-0.863</td>
<td>-2.135</td>
<td>-1.354</td>
<td>-2.004</td>
<td>-2.029</td>
<td></td>
</tr>
<tr>
<td>PP test static with trend</td>
<td>-2.687</td>
<td>-2.148</td>
<td>-1.700</td>
<td>-2.979</td>
<td>-1.471</td>
<td>-1.299</td>
<td>-1.304</td>
<td>-2.225</td>
<td>-1.487</td>
<td></td>
</tr>
<tr>
<td>ARIMA (0,1,0)</td>
<td>(0.1,0)</td>
<td>(1,1,0)</td>
<td>(1,1,0)</td>
<td>(1,1,0)</td>
<td>(0,1,0)</td>
<td>(0,1,0)</td>
<td>(0,1,0)</td>
<td>(0,1,0)</td>
<td>(0,1,0)</td>
<td></td>
</tr>
<tr>
<td>Runs test (z value)</td>
<td>0.463</td>
<td>-3.372</td>
<td>-2.551</td>
<td>-2.251</td>
<td>-0.296</td>
<td>-1.079</td>
<td>2.033</td>
<td>-0.574</td>
<td>-2.264</td>
<td></td>
</tr>
<tr>
<td>P-value</td>
<td>[0.642]</td>
<td>[0.000]</td>
<td>[0.010]</td>
<td>[0.024]</td>
<td>[0.766]</td>
<td>[0.280]</td>
<td>[0.042]</td>
<td>[0.565]</td>
<td>[0.023]</td>
<td></td>
</tr>
</tbody>
</table>
not follow random walk hypothesis in Other Service, Metal & Engineering, and Forest according to ARIMA test, reported in Table 4.

The Runs test is another approach to test and detect statistical dependencies (randomness) which may not be detected by the auto-correlation test. Table 4 reports that the $z$ statistics is greater than $\pm 1.96$ and negative for Other Service, Metal & Engineering, Forest and HEX, which means that the observed number of runs is fewer than the expected number of runs with observed significance level. But the $z$ statistics is greater than $\pm 1.96$ and positive for Trade. Thus we can conclude that the price series of Other Service, Metal & Engineering, Forest, Trade and HEX index do not follow random walk hypothesis.

Believers in chartist theories may think that stock returns are positively correlated in Other Service, Metal & Engineering, and Forest; evidence of arbitrage opportunity. It is well known that nonsynchronous trading is an important source of positive autocorrelation observed in short horizon returns of portfolios (Lo and MacKinlay (1990a) and Kadlec and Patterson (1999)). Samuelson (1965) notes that the efficient capital markets theory relates to the martingale model or fair game, a game which is neither in our favor nor our opponent’s, not with the random walk hypothesis. The martingale theorem$^{17}$ rules out any dependence of the $R_{t,i}$, whereas the random walk model rules out this and also dependence involving the higher moments of $R_{t,i}$. The evidence of higher moment dependencies of $R_{t,i}$ is reported in Table 5 and in Table 6.

Table 5 gives some preliminary diagnostics of the statistical significance of the mean impact curve using the joint Lagrange Multiplier tests. In performing the MIC tests, the effect of $^{17}$ The martingale hypothesis states that tomorrow’s price is expected to be equal to today’s price, given the asset’s entire price history. Alternatively, the asset’s expected price change is zero when conditioned on the asset’s price history.
holidays on returns is taken into account, defined as a dummy variable that takes the value of one on a trading day immediately after a holiday and zero elsewhere\textsuperscript{18}. This is formally achieved by augmenting the first stage regression of the tests to include a constant and the holiday dummy, and using the residuals from this regression in the subsequent stages of the tests to condition the results for any effects from holidays\textsuperscript{19}. In general, all three tests give the same qualitative results with few exceptions. Four of the nine equities (HEX, Other Service, Forest and Metal & Engineering) exhibit significant mean impact curves at the 5\% level. The efficient version of the test finds Bank & Finance has a significant MIC structure at the 5\% level, while Trade has a significant MIC structure at the 10\% level. All three tests find no significant evidence of any structure in the mean for Telecom & Electronics, Food and Other Industry, which is consistent with the descriptive statistics presented in Table 3.

Table 6 gives some preliminary diagnostics of the conditional volatility structure based on the Ljung-Box test applied to the squared returns and the Engle and Ng (1993) asymmetry class of tests. The Ljung-Box test of the squared returns shows significant evidence of autocorrelation at 5 lags (\(LB (5)\)) and 10 lags (\(LB (10)\)), for all nine equities. The joint Engle-Ng test (last two rows) shows strong evidence of asymmetries in the conditional variance of all nine equities. Inspection of the individual tests shows that the negative size bias specification test is statistically significant for all nine returns. The sign bias test is also significant for the HEX index.

\textsuperscript{18} Tests for day-of-the week effects are performed, but are found to be insignificant for all nine returns series. In contrast, tests for the effects on holidays in returns were also carried out and found to be statistically significant for some of the nine return series.

\textsuperscript{19} The tests were also performed without the holiday dummy and reveal no qualitative differences from the results reported in Table 5.
The table below presents the MIC (mean impact curve) tests of daily stock returns. The returns are logarithmic returns (\( R_{t,j} \)) measured in percentage, from the Helsinki Stock Exchange for the period of 2nd January 1997 to 30th December 2003. Three tests are reported: the Inefficient test, the Efficient test and the White Adjusted test. The inefficient test consists of first regressing \( R_{t,j} \) on a constant and the holiday dummy (\( d_1 \)) to get the residual \( u_{t,j} \). The second step involves regressing \( u_{t,j} \) on a constant, \( u_{t-1,j} \), \( u_{t-1,j}^2 \), \( u_{t-1,j}^3 \) and \( d_1 \). The test statistic is given by \( TR^2 \) where \( T \) is the number of observations and \( R^2 \) is the coefficient of determination from the second stage regression. The Efficient test consists of first estimating the GJR (1, 1) model where the mean contains a constant and \( d_1 \). The second stage consists of regressing \( u_{t,j} \) on a constant, \( u_{t-1,j} \), \( u_{t-1,j}^2 \), \( u_{t-1,j}^3 \) and \( d_1 \), where all variables are weighted by the inverse of the standard deviation of the residuals obtained from the first step. The test statistic is given by \( TR^2 \) as in the inefficient test. The White Adjusted test is obtained by first regressing \( R_{t,j} \) on a constant and \( d_1 \), to get the residual \( u_{t,j} \). The second step involves regressing \( \ln(e_{t,j}^2) \) on a constant, \( u_{t-1,j} \), \( u_{t-1,j}^2 \), \( u_{t-1,j}^3 \), which is used to compute an estimate of the residual variance. The third step consists of regressing \( u_{t,j} \) on a constant, \( u_{t-1,j} \), \( u_{t-1,j}^2 \), \( u_{t-1,j}^3 \) and \( d_1 \), where all variables are weighted by the inverse of the standard deviation of the residuals obtained from the second step. The test statistic is given by \( TR^2 \) as before. All statistics are distributed asymptotically under the null hypothesis as chi-squared with three degrees of freedom.

<table>
<thead>
<tr>
<th>Sample Statistics</th>
<th>Bank Finance</th>
<th>Other Service</th>
<th>Metal &amp; Engineering</th>
<th>Forest</th>
<th>Other Industry</th>
<th>Telecom &amp; Electronics</th>
<th>Trade</th>
<th>Food</th>
<th>HEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inefficient</td>
<td>21.169</td>
<td>29.596</td>
<td>21.890</td>
<td>47.685</td>
<td>3.571</td>
<td>6.389</td>
<td>11.150</td>
<td>0.668</td>
<td>29.848</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.312]</td>
<td>[0.094]</td>
<td>[0.011]</td>
<td>[0.881]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Efficient</td>
<td>8.384</td>
<td>33.866</td>
<td>17.646</td>
<td>33.575</td>
<td>1.756</td>
<td>4.084</td>
<td>7.516</td>
<td>3.221</td>
<td>11.447</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.039]</td>
<td>[0.000]</td>
<td>[0.001]</td>
<td>[0.000]</td>
<td>[0.625]</td>
<td>[0.252]</td>
<td>[0.057]</td>
<td>[0.359]</td>
<td>[0.010]</td>
</tr>
<tr>
<td>White Adj.</td>
<td>5.771</td>
<td>27.355</td>
<td>18.647</td>
<td>27.047</td>
<td>1.322</td>
<td>6.218</td>
<td>7.845</td>
<td>0.657</td>
<td>8.554</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.123]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.724]</td>
<td>[0.101]</td>
<td>[0.049]</td>
<td>[0.883]</td>
<td>[0.036]</td>
</tr>
</tbody>
</table>

Table 5
This table presents the volatility diagnostic tests of daily stock returns from the Helsinki Stock Exchange for the period of 2nd January 1997 to 30th December 2003. The returns are logarithmic rates of returns measured in percentage (multiplied by 100). Ljung-Box (n) is the Ljung-Box (LB) test statistics for n\textsuperscript{th} order autocorrelation of squared returns. The volatility specification test statistics, proposed by Engle and Ng (1993), are used to test for asymmetries in the second moments of the return series. First, the daily return \( R_{t,i} \) is regressed on a constant and \( R_{t,i-1} \) to obtain the residuals \( \epsilon_{t,i} \) to estimate these tests. This table reports the slope coefficient and P-value from the regression of the squared residuals on (respectively) (1) an indicator variable which takes the value one if the residual is negative and zero otherwise, (2) the product of the residual and an indicator variable that takes the value one if the residual is negative and otherwise zero and (3) the product of this indicator variable and residual. The joint test is the LM test for adding these three variables into the regression of the squared residuals follows a chi-square distribution with 3 degrees of freedom.

<table>
<thead>
<tr>
<th>Sample Statistics</th>
<th>Bank Finance</th>
<th>Other Service</th>
<th>Metal &amp; Engineering</th>
<th>Forest</th>
<th>Other Industry</th>
<th>Telecom &amp; Electronics</th>
<th>Trade</th>
<th>Food</th>
<th>HEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>LB (5) for squares</td>
<td>112.286</td>
<td>87.624</td>
<td>96.333</td>
<td>82.915</td>
<td>67.075</td>
<td>33.768</td>
<td>104.428</td>
<td>18.544</td>
<td>82.319</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.002]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>LB (10) for squares</td>
<td>153.068</td>
<td>115.388</td>
<td>110.813</td>
<td>87.870</td>
<td>78.003</td>
<td>50.898</td>
<td>170.840</td>
<td>27.831</td>
<td>95.250</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.001]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Sign bias test</td>
<td>0.089</td>
<td>0.039</td>
<td>0.088</td>
<td>0.273</td>
<td>0.080</td>
<td>0.239</td>
<td>0.037</td>
<td>0.331</td>
<td>0.434</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.373]</td>
<td>[0.738]</td>
<td>[0.411]</td>
<td>[0.014]</td>
<td>[0.391]</td>
<td>[0.030]</td>
<td>[0.698]</td>
<td>[0.087]</td>
<td>[0.001]</td>
</tr>
<tr>
<td>Negative size bias test</td>
<td>-0.337</td>
<td>-0.194</td>
<td>-0.458</td>
<td>-0.346</td>
<td>-0.299</td>
<td>-0.144</td>
<td>-0.258</td>
<td>-0.554</td>
<td>-0.383</td>
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<td>[0.000]</td>
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<td>0.108</td>
<td>0.125</td>
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the Telecom & Electronics and the Forest, at the 5% level and Food at the 10% level, as is the positive size bias test for Other Service at the 5% level and Bank & Finance at the 10% level. These results suggest that the asymmetric conditional variance model could be an appropriate specification to capture the time variation and asymmetries in the conditional variance of Finnish equity returns.

To summarize, higher moment dependencies of return series are present in the Finnish stock market. Thus the departure from the pure random walk hypothesis is not evidence of market inefficiency. The presence of conditional heteroskedasticity is inconsistent with the random walk model but does not violate the martingale process. Similar to the tests of the random walk hypothesis, the tests of the weak form of market efficiency mostly concerned with the forecast power of past returns and this category covers the more general area of tests for return predictability (Fama (1970)). The evidence of return predictability does not, however, violate the weak form of efficient market hypothesis unless there are unexploited trading opportunities in the market in excess of transaction cost.
Chapter 6

Empirical findings of various volatility models

Standard GARCH (1, 1) with EGARCH (1, 1), GJR (1, 1) and WGARCH (1, 1) are applied to the daily return series of eight industries together with the overall HEX listed on the Finnish stock market to compare and demonstrate the empirical properties of these models. The estimation and testing results of these parametric volatility models for the full sample period from 2nd January 1997 to 30th December 2003 are reported in this chapter, to select the best fitted model. The differences between the models are highlighted by comparing the news impact curves of these volatility models. In addition to this, the news sensitivity of different indices is compared here by comparing the steepness of the news impact curve.

Appendix A reports the maximum likelihood estimates of the parameters describing GARCH (1, 1), EGARCH (1, 1), GJR (1, 1) and WGARCH (1, 1) models. The auto-regressive coefficient $c_1$ is insignificant for all industries except Other Service, Metal and Engineering, Forest, and Trade according to EGARCH, GJR, and WGARCH estimates. The parameter $c_1$ is also significant in HEX for EGARCH and GJR. It would appear that for these indices, the martingale assumption is violated since future returns are predictable on the basis of current information. However, this statement should be qualified in light of the different degrees of liquidity that may characterize each index. It is very likely that the indices mentioned above are less liquid than the rest of the markets. The reported $c_1$ can be biased due to nonsynchronous trading and not a predictable pattern of stock return (Lo and MacKinlay (1988)).

The parameters describing the conditional variance process $\alpha_0$, $\alpha_1$ and $\beta_1$ are highly significant in all indices for GARCH, EGARCH, GJR and WGARCH except in Trade
where the parameter $\alpha_0$ of EGARCH is insignificant. This implies that current volatility is a function of last period’s squared innovation and last period’s volatility or, equivalently, the conditional variance is updated in the light of new information and the weight given to the last squared innovation is equal to $\alpha_1$. The autoregressive nature of volatility is important for the evaluation of derivative securities, such as options and options on futures, where ex-ante volatility measures are critical inputs.

The parameter $\varphi$ is highly significant (at the 5% level) in all indices for EGARCH and GJR. The significant value of $\varphi$ means that negative returns (market declines) are associated with higher volatility than positive returns (market advances) of an equal magnitude. The opposite would be true if $\varphi$ were positive. A zero value of $\varphi$ would imply that only magnitude effect matters. That means that positive and negative shocks of an equal magnitude exert the same impact on the stock return volatility. Therefore, EGARCH and GJR allow good news and bad news to have different impacts on volatility, while standard GARCH and WGARCH do not.

The news impact curves for GARCH, EGARCH and GJR of HEX are reported in Figure 7. The qualitative differences between these models can be compared by constructing their news impact curves. The news impact curve of GARCH is symmetric and passes through the origin, i.e., centered at $\varepsilon_{s,t-1}$ equal to zero, reported in Figure 7. Depending on the values of $\alpha_1$, $\varphi$ and unconditional standard deviation $\sigma$, the two sides of EGARCH news impact curve can be either steeper or less steep than the GARCH news impact curve. The news impact curve of GJR is centered at $\varepsilon_{s,t-1}$ equal to zero, but has different slopes for its positive and negative sides. Figure 7 shows that the quadratic form GJR news impact curve increases on both sides but increases more on the negative side than on the positive side. This characteristic is also true for EGARCH, but increases exponentially for its positive and negative
Figure 7. The news impact curves of GARCH (1, 1) model, EGARCH (1, 1) model and GJR (1, 1) model for HEX index. The solid line is the GARCH (1, 1) news impact curve. The dark dashed line is the EGARCH (1, 1) news impact curve. The light dashed line is the GJR (1, 1) news impact curve. The intercept term of the news impact curve is assumed to be fixed for each model to analyze the slope of the news impact curve. The equation for the GARCH (1, 1) news impact curve is

\[ \sigma_{i,t}^2 = A + \alpha \varepsilon_{i,t-1}^2, \]

where \( \sigma_{i,t}^2 \) is the conditional variance at time \( t \) and the intercept term \( A = \alpha_0 + \beta \sigma^2 \). The parameter \( \alpha_0 \) is constant. The term \( \varepsilon_{t-1} \) is the unpredictable return at time \( t-1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta \) is the parameter for \( \sigma_{i,t}^2 \). The shape of the GARCH news impact curve is indicative of cases with \( 0 \leq \alpha < 1, 0 \leq \alpha < 1, 0 \leq \beta < 1 \) and \( \sigma > 0 \).
The equation for the EGARCH (1, 1) news impact curve is

\[
\sigma^2_t = A \exp \left[ \alpha_1 \left( \frac{1 + \varphi}{\sigma} \right) \epsilon_{t-1} \right], \text{ when } \epsilon_{t-1} \geq 0
\]

\[
\sigma^2_t = A \exp \left[ \alpha_1 \left( \frac{\varphi - 1}{\sigma} \right) \epsilon_{t-1} \right], \text{ when } \epsilon_{t-1} < 0
\]

where \( \sigma^2_t \) is the conditional variance at time \( t \) and the intercept term \( A = \exp \left( \alpha_0 - \alpha_1 \sqrt{2/\pi} \right) \sigma^2 \). The parameter \( \alpha_0 \) is constant. The term \( \epsilon_{t-1} \) is the unpredictable return at time \( t-1 \). \( \sigma \) is the unconditional return standard deviation, \( \beta \) is the parameter for \( \sigma^2_t \). The shape of the EGARCH news impact curve is indicative of cases with \( 0 \leq \alpha_0 < 1, 0 \leq \alpha_1 < 1, 0 \leq \beta < 1, \sigma > 0 \) and more importantly \( \varphi < 0 \).

The equation for the GJR (1, 1) news impact curve is

\[
\sigma^2_t = A + \alpha_1 \epsilon^2_{t-1}, \text{ when } \epsilon_{t-1} \geq 0
\]

\[
\sigma^2_t = A + (\alpha_1 + \beta) \epsilon^2_{t-1}, \text{ when } \epsilon_{t-1} < 0
\]

where \( \sigma^2_t \) is the conditional variance at time \( t \) and the intercept term \( A = \alpha_1 + \beta \). The parameter \( \alpha_1 \) is constant. The term \( \epsilon_{t-1} \) is the unpredictable return at time \( t-1 \). \( \sigma \) is the unconditional return standard deviation, \( \beta \) is the parameter for \( \sigma^2_t \). The shape of the GJR news impact curve is indicative of cases with \( 0 \leq \alpha_0 < 1, 0 \leq \alpha_1 < 1, 0 \leq \beta < 1, \sigma > 0 \), more importantly \( \varphi > 0 \).

Sides. Therefore, asymmetric volatility models capture the leverage effect discovered by Black (1976) by allowing a steeper slope on the negative side than on the positive side of the news impact curve.
Appendix B represents the news impact curves of GARCH (1, 1), EGARCH (1, 1) and GJR (1, 1) for each index. WGARCH considers the asymmetric release of information rather than asymmetric information on the conditional volatility process. To capture the asymmetry in releases of information on different days, two indicator variables are introduced. These parameters are $\varphi_1$ for Fridays and $\varphi_2$ for Thursdays. The term $\varphi_2$ is negative and significant at 1% in Forest, Telecom and Electronics, HEX, and at 5% in Bank and Finance (see Appendix A). It is positive and significant at 1% in Food and at 5% in Trade. The parameter $\varphi_1$ which captures the Friday effect, is significant only in Food and HEX at the 1% level. This evidence leads to the conclusion that releases of information are not symmetric during week days. The estimated Otherdays’, Mondays’ and Fridays’ news impact curves of HEX are reported in Figure 8.

The news parameters of Thursdays and Fridays are statistically significant with negative sign in HEX index (see Appendix A). Thus Otherdays’ news impact curve is much steeper than Mondays’ and Fridays’ news impact curves. This means that news from Thursdays and Fridays decrease volatility of Fridays and Mondays respectively. Therefore, the risk (volatility) is, for a given return, higher on Otherdays than on Fridays and Mondays. But Thursdays’ news reduce volatility more than Fridays’ news. Therefore Mondays’ news impact curve is steeper than that of Fridays’. It is very likely that news releases on Fridays contain more bad information about the market than on Thursdays. These results are consistent with the findings of Damodaran (1989).

Mondays’ and Otherdays’ news impact curves are much steeper than Fridays’ news impact curve in all industries except in Food and Trade, reported in Appendix C. Fridays’ news impact curve is much steeper than Otherdays’ news impact curves in Trade.
Figure 8. Otherdays’ news impact curve, Mondays’ news impact curve and Fridays’ news impact curve of WGARCH (1, 1) model for HEX index. The solid line is the Otherdays’ news impact curve. The light dashed line is the Mondays’ news impact curve. The dark dashed line is the Fridays’ news impact curve. The equation for the Otherdays’ news impact curve is

\[ \sigma_{i,t}^2 = A + \alpha \cdot \epsilon_{i,t-1}^2 \]

where \( A = \alpha_0 + \beta \cdot \sigma^2 \), the parameter \( \alpha_0 \) is a constant term and \( \sigma^2 \) is the unconditional return variance. The term \( \epsilon_{i,t-1} \) is the unpredictable return at time \( t-1 \), \( \beta \) is the parameter for \( \sigma_{i,t}^2 \). The shape of the Otherdays’ news impact curve is indicative of cases with \( 0 \leq \alpha_0 < 1 \), \( 0 \leq \alpha < 1 \), \( 0 \leq \beta < 1 \), and unconditional return standard deviation \( \sigma > 0 \).
The equation for the Mondays’ news impact curve is

$$\sigma^2_{t-1} = A + (\alpha_i + \varphi) \varepsilon^2_{i-1},$$

where $A = \alpha_o + \beta_1 \sigma^2$, the parameter $\alpha_o$ is a constant term and $\sigma^2$ is the unconditional return variance. The term $\varepsilon_{i-1}$ is the unpredictable return at time $t-1$, $\beta_1$ is the parameter for $\alpha^2_{t-1}$. The shape of the Mondays’ news impact curve is indicative of cases with $0 \leq \alpha_i < 1$, $0 \leq \alpha_i < 1$, $0 \leq \beta < 1$, $\sigma > 0$ and more importantly on the constant parameter $\varphi$.

The equation for the Fridays’ news impact curve is

$$\sigma^2_{t-1} = A + (\alpha_i + \varphi) \varepsilon^2_{i-1},$$

where $A = \alpha_o + \beta_1 \sigma^2$, the parameter $\alpha_o$ is a constant term and $\sigma^2$ is the unconditional return variance. The term $\varepsilon_{i-1}$ is the unpredictable return at time $t-1$, $\beta_1$ is the parameter for $\alpha^2_{t-1}$. The shape of the Fridays’ news impact curve is indicative of cases with $0 \leq \alpha_i < 1$, $0 \leq \alpha_i < 1$, $0 \leq \beta < 1$, $\sigma > 0$ and more importantly on the constant parameter $\varphi_2$.

The parameters $\varphi_1$ and $\varphi_2$ have a positive sign with $\varphi_1 > \varphi_2$ in Food. That means that Fridays’ news have higher impact on increasing volatility on Mondays than Thursdays’ news on Fridays. Further research should be done to explain why these industries are different from other indices. So far we can only speculate. Probably in these categories of industries, companies store inventory on Fridays for the weekend because Saturday and Sunday are closed. The inventory of stocks may increase the uncertainty of future prospects, which is reflected in Friday’s news. The anxieties about Friday’s news are reflected by the higher volatility of Mondays.
To summarize, the news impact curve of GARCH is symmetric. Unlike GARCH, EGARCH captures asymmetry in the effect of news on conditional volatility because it has a steeper slope on its negative side than on its positive side. GJR also captures asymmetry in a similar fashion and centered at $\varepsilon_{t-1} - B = 0$. W GARCH, on the other hand, captures asymmetric release of information by allowing the news impact curves to have different slopes for different days.

I now analyze the news impact curves of different volatility models in each index and also compare the news sensitivity of different indices for each volatility model. Steepness of the news impact curve is used as a measure of news sensitivity. The steeper the news impact curve the higher the news sensitivity. The steepness of the news impact curves for GARCH, GJR depends upon the parameter $\alpha$ and $\phi$. But for the case of EGARCH, it depends upon the parameters $\alpha$, $\phi$, and $\sigma$.

The implied volatility level of each model at several pre-specified values for $\varepsilon_{t-1}$ is used to examine the news impact curves of various volatility models in each index. The estimate of $\sigma_{t}^2$ is equal to 15.087 for GARCH, 147.521 for EGARCH and 13.669 for GJR for an $\varepsilon_{t-1}$ equal to 10 in Telecom and Electronics and for an $\varepsilon_{t-1}$ equal to -10, these estimates are 15.087, 191.576, and 16.569 for GARCH, EGARCH and GJR respectively. Similarly in Metal and Engineering for an $\varepsilon_{t-1}$ equal to 10, estimates of $\sigma_{t}^2$ are 19.044, 8.204 and 8.874 and for an $\varepsilon_{t-1}$ equal to -10, these estimates are 19.044, 47.450 and 24.874 for GARCH, EGARCH and GJR respectively. Thus standard GARCH relative to EGARCH tends to understate $\sigma_{t}^2$ for a large negative value of $\varepsilon_{t-1}$ and overstate $\sigma_{t}^2$ for a large positive value of $\varepsilon_{t-1}$ in this industry.

If the curves were extrapolated, EGARCH would give higher variance in both directions because the exponential curve eventually dominates the quadratic. EGARCH overstates $\sigma_{t}^2$ for large positive and negative values for $\varepsilon_{t-1}$ because of high unconditional variance in Telecom and Electronics. Let us assume the term $A$ equal to 2, to compare the news sensitivity of different indices for each volatility model. Implied volatility
Table 7

This table reports news impact curve estimates of various volatility models. Here the value of the current volatility, $\sigma_t^2$, as a function of the past return shock, $\varepsilon_{t-1}$, assuming the intercept term of the news impact curve is equal to 2 for each index. The values are given for various predictable volatility models for the daily return series of the Helsinki Stock Exchange. The sample period is from 2nd January 1997 to 30th December 2003.

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<th>$\varepsilon_{t-1}$</th>
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<th>Other Service</th>
<th>Metal &amp; Engineering</th>
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<th>Telecom &amp; Electronics</th>
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<td>2.571</td>
<td>3.945</td>
<td>3.585</td>
<td>3.208</td>
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<td></td>
<td>GJR $\sigma_t^2$</td>
<td>5.300</td>
<td>5.975</td>
<td>7.900</td>
<td>6.725</td>
<td>4.625</td>
<td>3.350</td>
<td>4.625</td>
<td>7.075</td>
<td>5.850</td>
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</tbody>
</table>

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estimates for each model of each index at several pre-specified values of $\varepsilon_{t,t-1}$ are summarized in Table 7.

Table 7 shows that the implied volatility $\sigma^2$ has the higher value in EGARCH compared to GARCH and GJR for a very small value of $\varepsilon_{t,t-1}$ equal to 0.5 (or -0.5). That means that the EGARCH news impact curve has a steeper slope compared to the GARCH and GJR news impact curve for very small values of $\varepsilon_{t,t-1}$ (see Appendix B). But this is not evident for large values of $\varepsilon_{t,t-1}$ in each index. Appendix B shows that the news impact curves of GARCH, EGARCH and GJR intersect each other. At the point of intersection the implied volatility estimate will be indifferent for each volatility model.

Table 7 also shows that the implied volatility estimates of a volatility model differ in each index for a single value of $\varepsilon_{t,t-1}$. For example, the implied volatility estimate of GJR is 7.900 in Metal and Engineering and 3.350 in Telecom and Electronics for a value of $\varepsilon_{t,t-1}$ equal to -5. That means that the news sensitivity of Metal and Engineering is higher than the news sensitivity of Telecom and Electronics according to GJR for that amount of news. This finding also holds for GARCH and EGARCH. The implied volatility estimates of GARCH and EGARCH are 6.450 and 10.711 respectively in Metal and Engineering for a value of $\varepsilon_{t,t-1}$ equal to -5. These estimates are 2.975 for GARCH and 2.571 for EGARCH in Telecom and Electronics for the same value of $\varepsilon_{t,t-1}$. Therefore, news affect each index differently and the news sensitivity estimate depends on the chosen volatility model.

The news impact curves of different indices estimated by GARCH, EGARCH and GJR are also presented in Figure 9, Figure 10 and Figure 11 respectively, where the term $A$ is assumed to be fixed for each index. These figures state that Metal and Engineering is the highest and Telecom and Electronics is the lowest news sensitive industry according to GARCH.
Figure 9. Comparison of news sensitivity of different indices according to GARCH (1, 1) model. The equation for the GARCH (1, 1) news impact curve is

\[ \sigma_{t,i} = A + \alpha \varepsilon_{t, -1}^2, \]

where \( \sigma_{t,i} \) is the conditional variance at time \( t \) and \( A = \alpha_0 + \beta \sigma^2 \). The parameter \( \alpha_0 \) is constant. The term \( \varepsilon_{t, -1} \) is the unpredictable return at time \( t - 1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta \) is the parameter for \( \sigma_{t,i} \). The news sensitivity is measured by the parameter \( \alpha \) assuming that the intercept term \( A \) is fixed for each index. News sensitivity is highest for Metal and Engineering followed by Food, Forest, Other Service, Bank and Finance, Other Industry, HEX, Trade, Telecom and Electronics in descending order.

EGARCH and GJR estimates. The news impact curves of WGARCH i.e., Mondays’, Fridays’ and Otherdays’ news impact curves are used to compare the news sensitivity of different indices.
Figure 10. Comparison of news sensitivity of different indices according to EGARCH (1, 1) model. The equation for the EGARCH (1, 1) news impact curve is

\[
\sigma_{t,i}^2 = A \exp \left[ \alpha_i \left( \frac{1 + \varphi}{\sigma} \right) \varepsilon_{t,i-1} \right], \text{ when } \varepsilon_{t,i-1} \geq 0
\]

\[
\sigma_{t,i}^2 = A \exp \left[ \alpha_i \left( \frac{\varphi - 1}{\sigma} \right) \varepsilon_{t,i-1} \right], \text{ when } \varepsilon_{t,i-1} < 0
\]

where \( \sigma_{t,i}^2 \) is the conditional variance at time \( t \) and \( A = \exp \left( \alpha_0 - \alpha_i \sqrt{2/\pi} \right) \sigma^{2i} \). The parameter \( \alpha_0 \) is constant.

The term \( \varepsilon_{t,i-1} \) is the unpredictable return at time \( t-1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta_i \) is the parameter for \( \sigma_{t,i}^2 \). Steepness of the news impact curve is measured by the coefficient of \( \varepsilon_{t,i-1} \). The coefficient of \( \varepsilon_{t,i-1} \) depends upon the parameters \( \alpha_i \), \( \varphi \) and \( \sigma \). The news sensitivity of different indices is determined by the steepness of the news impact, assuming the intercept term \( A \) is fixed for each index. News sensitivity is highest for Metal and Engineering followed by Other Industry, Trade, Forest, Bank and Finance, Food, HEX, Other Service, Telecom and Electronics in descending order.
Figure 11. Comparison of news sensitivity of different indices according to GJR (1, 1) model. The equation for the GJR (1, 1) news impact curve is

\[
\sigma_{i,t}^2 = \sigma_0^2 + \alpha \varepsilon_{i,t-1}^2, \quad \text{when} \quad \varepsilon_{i,t-1} \geq 0
\]

\[
\sigma_{i,t}^2 = \sigma_0^2 + (\alpha + \varphi)\varepsilon_{i,t-1}^2, \quad \text{when} \quad \varepsilon_{i,t-1} < 0
\]

where \(\sigma_{i,t}^2\) is the conditional variance at time \(t\) and \(A = \sigma_0^2 + \beta \sigma^2\). The parameter \(\alpha_0\) is constant. The term \(\varepsilon_{i,t-1}\) is the unpredictable return at time \(t-1\), \(\sigma\) is the unconditional return standard deviation, \(\beta\) is the parameter for \(\sigma_{i,t}^2\). The steepness of the news impact curve is measured by the coefficient of \(\varepsilon_{i,t-1}^2\). The coefficient of \(\varepsilon_{i,t-1}^2\) depends upon the parameters \(\alpha\) and \(\varphi\). The news sensitivity of different indices is determined by the steepness of the news impact, assuming that the intercept term \(A\) is fixed for each index. News sensitivity is highest for Metal and Engineering followed by Food, Forest, Other Service, HEX, Bank and Finance, Other Industry, Trade, and Telecom and Electronics in descending order.

Otherdays’, Mondays’ and Fridays’ news impact curves of the WGARCH model are plotted in Figures 12, 13 and 14 respectively. Graphical analysis states that Metal and Engineering
Figure 12. Comparison of news sensitivity of different indices, considering Otherdays’ news impact curve.

The equation for the Otherdays’ news impact curve is

\[ \sigma_{t,t-1} = A + \alpha_1 \epsilon_{t,t-1} \]

where \( A = \alpha_0 + \beta_1 \sigma^2 \) and the parameter \( \alpha_0 \) is a constant term. The term \( \epsilon_{t,t-1} \) is the unpredictable return at time \( t-1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta_1 \) is the parameter for \( \sigma_{t,t-1} \). The news sensitivity is measured by the parameter \( \alpha \), assuming the intercept term \( A \) is fixed for each index. News sensitivity is highest for Metal and Engineering followed by Forest, HEX, Food, Other Service, Bank and Finance, Other Industry, Trade, Telecom and Electronics in descending order considering Otherdays’ news impact curve.

is the most and Telecom and Electronics is the least sensitive industry, considering Otherdays’ news, reported in Figure 12. But the coefficients capturing Thursdays’ and Fridays’ news are insignificant in Metal and Engineering. Probably this industry does not release valuable information on Thursdays and Fridays. Figure 13 shows that Mondays’ news impact curve is steeper for Food than for HEX. Thus, Fridays’ news have produced highest impact in increasing \( \sigma_{t,t-1} \) of Mondays in Food. Thursdays’ news have the highest impact in decreasing
Figure 13. Comparison of news sensitivity of different indices, considering Mondays’ news impact curve.

The equation for the Mondays’ news impact curve is

\[ \sigma_{j,t}^2 = A + (\alpha_i + \phi_i) \epsilon_{j,t-1}^2 \]

where \( A = \alpha_0 + \beta_\sigma \) and the parameter \( \alpha_i \) is a constant term. The term \( \epsilon_{j,t-1}^2 \) is the unpredictable return at time \( t-1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta_i \) is the parameter for \( \sigma_{j,t}^2 \). The news sensitivity is measured by the coefficient of \( \epsilon_{j,t-1}^2 \) assuming the intercept term \( A \) is fixed for each index. The coefficient of \( \epsilon_{j,t-1}^2 \) depends on the parameters \( \alpha_i \) and \( \phi_i \). News sensitivity is highest for Food and lowest for HEX considering Mondays’ news impact curve.

The volatility of Fridays in Telecom and Electronics according to WGARCH estimates reported in Figure 14. In this industry, Fridays’ news impact curve is horizontal. This means that Thursdays’ news fully compensate the Otherdays’ news. In other words, news from Thursdays decrease the same amount of volatility as is increased by news of Otherdays. Probably good corporate news and news from different institutions (such as the Federal Reserve or the Bureau of Labor Statistics) on Thursdays reduce volatility on Fridays, stimulating
Figure 14. Comparison of news sensitivity of different indices considering Fridays’ news impact curve.

The equation for the Fridays’ news impact curve is

\[ \sigma_{ij,t} = A + (\alpha_i + \phi_2) \varepsilon_{t-1} \]

where \( A = \alpha_0 + \beta_1 \sigma^2 \) and parameter \( \alpha_0 \) is the constant term. The term \( \varepsilon_{t-1} \) is the unpredictable return at time \( t-1 \), \( \sigma \) is the unconditional return standard deviation, \( \beta_1 \) is the parameter for \( \sigma_{ij,t} \). The steepness of the news impact curve depends upon the parameters \( \alpha_0 \) and \( \phi_2 \). The news sensitivity is measured by the steepness of the news impact, assuming the intercept term \( A \) is fixed for each index. News sensitivity is highest for Food followed by Trade, Forest, Bank and Finance, HEX, Telecom and Electronics in descending order considering Fridays’ news impact curve.

Investors to buy stocks on Fridays. Then higher demand raises the stock price and decreases the debt equity ratio and consequently reduces volatility. Institutional investors are much more active than individuals in collecting information. Their trading activities are therefore much more intense on Fridays than on other days of the week. This phenomenon is also documented by Miller (1988) and Lakonishok and Maberly (1990). The analysis of the news impact curve states...
Table 8

This table reports the summary statistics of the estimated conditional variances of the daily return series from various predictable volatility models for the period of 2nd January 1997 to 30th December 2003. Mean and Variance are the mean and the variance of the estimated conditional variance series respectively. The statistic Skewness is the coefficient of skewness and the statistic Kurtosis is the coefficient of kurtosis of the estimated conditional variances. For a standard normal variable, the value of the coefficient of skewness is zero and the value of the coefficient of kurtosis is 3. Maximum and Minimum are the maximum value and the minimum value of the estimated conditional variance series respectively.

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<td>GJR</td>
<td>WGARCH</td>
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<td>3.695</td>
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<td>4.606</td>
<td>4.527</td>
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<tr>
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<tr>
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<td>13.610</td>
<td>17.202</td>
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<td>0.954</td>
<td>1.377</td>
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## Table 8 – Continued

Industry-sorted Portfolios and The HEX index

<table>
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<tr>
<th>Parameters</th>
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<th>Metal and Engineering</th>
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</thead>
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<td>Mean</td>
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<th>Parameters</th>
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<th>Trade</th>
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<td>Skewness</td>
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<tr>
<td>Kurtosis</td>
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<tr>
<td>Maximum</td>
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<td>Minimum</td>
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<td>EGARCH</td>
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</tr>
<tr>
<td>Minimum</td>
<td>0.809</td>
<td>0.664</td>
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</table>
This table reports the diagnostic tests of the different volatility models. Skewness and Kurtosis are the estimated skewness and kurtosis of the estimated standardized residuals from the mean generating equation 
\( R_{t,i} = c + c_i R_{t,i-1} + \varepsilon_{t,i} \). For a standardized variable, the value of the coefficient of skewness is zero and the value of the coefficient of kurtosis is three. The Sign bias test, Negative size bias test, Positive size bias test and Joint tests are those suggested by Engle and Ng (1993). This table reports the slope coefficient and P-value from the regression of the squared standardized residuals on (respectively) (1) an indicator variable which takes a value of one if the residual is negative and otherwise zero, (2) the product of the residual and an indicator variable that takes a value of one if the residual is negative and otherwise zero, (3) the product of this indicator variable and residual. The joint test is the LM test for adding these three variables in the regression of the squared standardized residual. The AR (1) coefficient is the slope coefficient from the regression of the fitted variance at time \( t \) on the fitted variance at time \( t-1 \).

<table>
<thead>
<tr>
<th>Test statistics</th>
<th>GARCH</th>
<th>EGARCH</th>
<th>GJR</th>
<th>WGARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skewness</td>
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<td>-0.066</td>
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<tr>
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<td>[0.254]</td>
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<td>1.425</td>
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<td>P-value</td>
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<td>[0.038]</td>
<td>[0.081]</td>
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<tr>
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<tr>
<td>P-value</td>
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<tr>
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Industry-sorted Portfolios and The HEX index
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<td>P-value</td>
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<td>Sign bias test</td>
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<tr>
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<td>Skewness</td>
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<tr>
<td>P-value</td>
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<tr>
<td>AR (1) coefficient</td>
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Table 9 – Continued

Industry-sorted Portfolios and The HEX index

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<tr>
<td></td>
<td>GARCH</td>
<td>EGARCH</td>
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<tr>
<td>Skewness</td>
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<td>3.962</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.037]</td>
<td>[0.265]</td>
</tr>
<tr>
<td>AR (1) coefficient</td>
<td>0.985</td>
<td>0.972</td>
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<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Test statistics</th>
<th>Food</th>
<th>HEX</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GARCH</td>
<td>EGARCH</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.604</td>
<td>0.864</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Sign bias test</td>
<td>0.176</td>
<td>0.126</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.276]</td>
<td>[0.465]</td>
</tr>
<tr>
<td>Negative size bias test</td>
<td>-0.154</td>
<td>-0.228</td>
</tr>
<tr>
<td>P-value</td>
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<td>[0.007]</td>
</tr>
<tr>
<td>Positive size bias test</td>
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<td>0.092</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.398]</td>
<td>[0.267]</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.282]</td>
<td>[0.012]</td>
</tr>
<tr>
<td>AR (1) coefficient</td>
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<td>0.979</td>
</tr>
<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
</tbody>
</table>

that GARCH, EGARCH, GJR and WGARCH are different from each other. Some summary statistics, including the mean, variance, skewness, kurtosis, maximum and minimum are produced for each of the estimated conditional variance series to better understand these different volatility models. They are reported in Table 8. These statistics along with some
Specification tests on the standardized residuals will help us to choose the best volatility model for the Finnish stock market.

Specification tests performed on the standardized residuals of GARCH, EGARCH, GJR and WGARCH are reported in Table 9. If the model is correctly specified the standardized residuals \( z_t \) should have zero mean and unit variance. The sample mean and variance of \( z_t \) suggest that this is the case for GARCH. This evidence holds true for EGARCH, GJR and WGARCH in each index (see Appendix A). Table 9 has displayed the skewness and kurtosis of standardized residuals of different volatility models. Properly specified GARCH, EGARCH, GJR and WGARCH should be able to significantly reduce the skewness and kurtosis evident in daily returns. Table 9 has shown that the level kurtosis of estimated standardized residuals has been significantly reduced but is significant in all indices. GJR performs better than other three models according to this diagnostic test.

The conditional variance series produced by GARCH has the lowest variation over time in most of the indices (see Table 8). The unconditional variance of estimated conditional variance produced by GARCH is the highest (13.317) in Food. GARCH estimated conditional variance ranges from 0.809 to 62.174 compared to ranges from 0.889 to 26.034 under GJR. The unconditional variances of estimated conditional variance series produced by GJR and EGARCH are 8.353 and 3.678 respectively. Thus GARCH will be the best proxy for estimating conditional variance in Food because GARCH estimated conditional variance has the highest variation over time (Engle and Ng (1993)). This fact is also suggested by the sign bias test, negative size bias test, positive size bias test and joint test statistics reported in Table 9. If we study the other indices (except Food and Trade) with the same logic we can observe that the GJR estimated conditional variance series has the highest variation over time compared to other models. Therefore GJR could be the best
model to estimate conditional variance (risk) on the Finnish stock market according to this diagnostic test.

Glosten, Jagannathan and Runkle (1993) document that the volatility model which gives the lowest volatility persistence will be treated as a better model. It is hard to compare the amount of persistence in variance that different volatility models like GARCH, GJR, EGARCH and WGARCH predict, because the parameterization of these models differs. One way to compare persistence in variance across models is to regress $\sigma_t^2$ on a constant and $\sigma_{t-1}^2$. GARCH and WGARCH produce the lower volatility persistence compared to EGARCH and GJR in most of the indices (see Table 9). But negative size bias test and joint test are significant in four out of nine indices for both GARCH and WGARCH. They are reported in Table 9. Especially in HEX, the sign bias test, negative size bias test, positive size bias test and joint test are highly significant for GARCH and WGARCH. Therefore, GARCH and WGARCH fail to capture size and sign effect of news adequately on the Finnish stock market.

The Ljung-Box statistic with 5 lags ($LB (5)$) and ($LB (10)$) of standardized residuals and squared standardized residuals estimated by EGARCH and GJR are insignificant in all indices (see Appendix A). GJR performs better than EGARCH according to the sign bias test, negative size bias test, positive size bias test and joint test reported in Table 9. Negative size bias test is marginally significant (at the 5% level) in only one index (Telecom and Electronics) out of nine for GJR (1, 1). By contrast EGARCH fails to capture the negative return shocks in the Bank and Finance, Forest, Food and HEX indices. The skewness is significant in six out of nine according to GJR estimate. This is not evidence of misspecification. Other studies assuming conditional normality encounter the same problem (e.g. Hamao, Masulis, and Ng (1990)). Conditional distributions that allow fat tails may solve this problem. Such distributions have been used in many studies, e.g. Booth et al. (1992),
Nelson (1991) among others. But the estimates obtained under the assumption of conditional normality will still be consistent and asymptotically normal, but the true standard errors may be underestimated (see Bollerslev and Wooldridge (1992)).

Glosten, Jagannathan and Runkle (1993) also show that the use of nominal interest rate in the conditional variance equation can also reduce the skewness and kurtosis of the estimated standardized residuals. The use of nominal interest rates in conditional variance models has some intuitive appeal. It has been observed since Fischer (1981) that the variance of inflation increases with its level. To the extent that short-term nominal interest rates embody expectations about inflation, they could be a good predictor of future volatility in excess returns. Using the information contained in the nominal interest rates, Fama and Schwert (1977), Campbell (1987) and Breen, Glosten and Jagannathan (1989) demonstrate that it is possible to forecast time periods when the excess return on stocks is relatively large and significantly less volatile. Giovannini and Jorion (1989) also examine the ability of nominal interest rates to predict changes in the volatility respectively of foreign exchange and stock returns.

To summarize, EGARCH and GJR seem to outperform the other models in capturing the dynamic behavior of stock returns. GJR performs better than EGARCH considering the sign bias test, negative size bias test, positive size bias test, joint test and other tests in most of the indices. Therefore the GJR model, proposed by Glosten, Jagannathan and Runkle in 1993, performs best in Finnish stock market and this model is used as a proxy for $\sigma_{t+1}^2$ in estimating the feedback trading model of Sentana and Wadhwani (1992).
Chapter 7
The feedback trading model estimates and the mean impact curve

Given the results of the volatility modeling, MIC and NIC tests presented in the previous chapters, the following trading model is now estimated for each of the return series

\[ R_{t,t} = \gamma_0 + \lambda \sigma^2_{t,t} + (\gamma_1 + \gamma_2 \sigma^2_{t,t})R_{t-1,t} + \delta HOL_{t,t} + \varepsilon_{t,t} \]

\[ \sigma^2_{t,t} = \alpha_1 + \alpha_2 \varepsilon^2_{t-1,t-1} + \varphi S_{t,t-1} \varepsilon^2_{t-1,t-1} + \beta_1 \sigma^2_{t-1,t-1} \]  \hspace{1cm} (58)

\[ \varepsilon_{t,t} \sim N(0, \sigma^2_{t,t}) \]

where \( HOL_{t,t} \) is the holiday dummy variable that takes a value of one on a trading day immediately after a holiday and elsewhere zero and \( S_{t,t-1} \) is the asymmetric dummy variable defined as

\[ S_{t,t-1} = \begin{cases} 
1 & : \varepsilon_{t-1,t} < 0 \\
0 & : \varepsilon_{t-1,t} \geq 0 
\end{cases} \]  \hspace{1cm} (59)

The term \( \sigma^2_{t,t} \) represents the conditional volatility. The intercept term \( \gamma_0 \) is the rate of return at which the demand for share by smart money holder is zero.

Parameter \( \lambda \) measures the risk premium. If parameter \( \lambda \) is positive then expected volatility increases the risk premium needed to induce smart money to hold shares in the market. There is general agreement that investors, within a given time period, require a larger expected return on a security that is riskier. However, there is no such agreement about the relationship between risk and return across time. Whether or not investors require a larger risk premium on average for investing in a security during times when the security is more risky remains an open
question. At first sight, it may appear that rational risk-averse investors would require a relatively larger risk premium during times when the payoff from the security is more risky. A large risk premium may not be required, however, because time periods which are relatively more risky could coincide with time periods when investors are better able to bear a particular type of risk.

If parameter $\lambda$ is negative, then expected volatility decreases the risk premium to the investors. This is reasonable, because the investors may want to save relatively more during periods when the future is more risky. If all the productive assets available for transferring income to carry the future risk and no risk free investment opportunities are available, then the price of the risky asset may be bid up considerably, thereby reducing the risk premium. Hence a positive as well as negative sign for the covariance between the conditional mean and conditional variance of the return on stocks would be consistent with theory.

Parameter $\gamma_1$ measures the degree of correlation of past and future returns due to nonsynchronous trading. The degree of feedback trading is measured by parameter $\gamma_2$. If parameter $\gamma_2$ is negative, then some individuals adopt positive feedback trading. Investors like positive feedback traders buy (sell) after price increases (decreases). In the conditional variance equation parameter $\alpha_i > 0$ is the constant term. $\beta_i > 0$ is the parameter for $\sigma_{i,t}^2$ term, $\alpha_i > 0$ is the parameter for $\epsilon_{i,t}^2$ term, parameter $\phi > 0$ captures the leverage effect discovered by Black (1976).
The table reported below presents the maximum likelihood estimates of the feedback trading model using daily logarithmic returns from the Helsinki Stock Exchange for the period of 2nd January 1997 to 30th December 2003. The univariate representation of the feedback trading model

\[ R_{t} = \gamma_{0} + \lambda \sigma_{t}^{2} + \left( \gamma_{1} + \gamma_{2} \sigma_{t-1}^{2} \right) R_{t-1} + \delta \text{HOL}_{t-1} + \varepsilon_{t} \]

\[ \sigma_{t}^{2} = \alpha_{0} + \alpha_{1} \varepsilon_{t-1}^{2} + \varphi \delta_{t-1} \varepsilon_{t-1}^{2} + \beta \sigma_{t-1}^{2} \]

\[ \varepsilon_{t} \sim N(0, \sigma_{t}^{2}) \]

The term \( R_{t} \) represents the daily logarithmic returns of the HEX and the industry-sorted portfolios. The term \( \text{HOL}_{t-1} \) is a holiday dummy variable that takes the value of one on a trading day immediately after a holiday and zero elsewhere.

The term \( \varepsilon_{t} \) is the unpredictable return at time \( t \) and \( \sigma_{t}^{2} \) is the conditional variance at time \( t \), which follows GJR (1, 1) process. The terms \( \gamma_{i} \geq 0, \lambda, 0 \leq \gamma_{1} < 1, \gamma_{2} < 0, 0 \leq \alpha_{0}, 0 \leq \alpha_{i} < 1, 0 \leq \beta_{i} < 1 \) and more importantly \( \varphi > 0 \) are constant parameters in the feedback trading model.

<table>
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<tr>
<th>Coefficients</th>
<th>Bank</th>
<th>Finance</th>
<th>Other</th>
<th>Service</th>
<th>Metal &amp; Engineering</th>
<th>Forest</th>
<th>Other</th>
<th>Industry</th>
<th>Industry</th>
<th>Trade</th>
<th>Telec &amp; Electronics</th>
<th>Trade</th>
<th>Food</th>
<th>HEX</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma_{0} )</td>
<td>-0.059</td>
<td>0.082</td>
<td>0.101</td>
<td>-0.046</td>
<td>0.131</td>
<td>0.192</td>
<td>0.029</td>
<td>0.036</td>
<td>0.087</td>
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<td>[0.367]</td>
<td>[0.112]</td>
<td>[0.699]</td>
<td>[0.154]</td>
<td>[0.187]</td>
<td>[0.592]</td>
<td>[0.511]</td>
<td>[0.247]</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>( \lambda )</td>
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<td>-0.005</td>
<td>-0.066</td>
<td>0.007</td>
<td>-0.055</td>
<td>-0.007</td>
<td>-0.013</td>
<td>-0.002</td>
<td>-0.001</td>
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<td></td>
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<tr>
<td>P-value</td>
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<td>[0.677]</td>
<td>[0.151]</td>
<td>[0.778]</td>
<td>[0.364]</td>
<td>[0.582]</td>
<td>[0.802]</td>
<td>[0.906]</td>
<td>[0.884]</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>( \gamma_{1} )</td>
<td>0.050</td>
<td>0.164</td>
<td>0.145</td>
<td>0.272</td>
<td>-0.006</td>
<td>0.103</td>
<td>-0.070</td>
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<td>0.155</td>
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<tr>
<td>P-value</td>
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<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.920]</td>
<td>[0.045]</td>
<td>[0.185]</td>
<td>[0.379]</td>
<td>[0.000]</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>( \gamma_{2} )</td>
<td>-0.008</td>
<td>-0.002</td>
<td>-0.026</td>
<td>-0.022</td>
<td>-0.009</td>
<td>-0.006</td>
<td>0.001</td>
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<tr>
<td>P-value</td>
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<td>[0.775]</td>
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<td>[0.957]</td>
<td>[0.508]</td>
<td>[0.001]</td>
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<tr>
<td>( \delta )</td>
<td>0.631</td>
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<td>0.586</td>
<td>0.219</td>
<td>0.331</td>
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<td>P-value</td>
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<td>[0.053]</td>
<td>[0.032]</td>
<td>[0.183]</td>
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<td>( \alpha_{0} )</td>
<td>0.180</td>
<td>0.203</td>
<td>0.194</td>
<td>0.456</td>
<td>0.081</td>
<td>0.093</td>
<td>0.037</td>
<td>0.122</td>
<td>0.104</td>
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<tr>
<td>P-value</td>
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<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.126]</td>
<td>[0.043]</td>
<td>[0.006]</td>
<td>[0.011]</td>
<td>[0.004]</td>
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<td></td>
</tr>
<tr>
<td>( \alpha_{1} )</td>
<td>0.067</td>
<td>0.066</td>
<td>0.071</td>
<td>0.054</td>
<td>0.032</td>
<td>0.023</td>
<td>0.046</td>
<td>0.063</td>
<td>0.061</td>
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<tr>
<td>P-value</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.002]</td>
<td>[0.005]</td>
<td>[0.101]</td>
<td>[0.006]</td>
<td>[0.014]</td>
<td>[0.053]</td>
<td>[0.000]</td>
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</tr>
<tr>
<td>( \varphi )</td>
<td>0.077</td>
<td>0.092</td>
<td>0.165</td>
<td>0.115</td>
<td>0.060</td>
<td>0.034</td>
<td>0.057</td>
<td>0.137</td>
<td>0.075</td>
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<tr>
<td>P-value</td>
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<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.002]</td>
<td>[0.039]</td>
<td>[0.010]</td>
<td>[0.000]</td>
<td>[0.012]</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>( \beta_{t} )</td>
<td>0.846</td>
<td>0.867</td>
<td>0.722</td>
<td>0.799</td>
<td>0.885</td>
<td>0.951</td>
<td>0.891</td>
<td>0.835</td>
<td>0.892</td>
<td></td>
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</tr>
<tr>
<td>P-value</td>
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<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
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<td>[0.000]</td>
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</tbody>
</table>
The results of estimating this model by maximum likelihood for each of the nine return series are given in Table 10, with p-values reported in parentheses. The calculations are performed using a gradient algorithm from the procedure MAXLIK in GAUSS Version 7.0. All derivatives are computed numerically with standard errors based on the inverse of the Hessian matrix.\(^{20}\)

The estimates of \(\gamma_2\) in Table 10 reveal strong evidence of a nonlinear structure arising from the feedback trading channel in the mean returns of the HEX and Forest portfolios at the 5% level, and in the Telecom & Electronics portfolio at the 10% level. In contrast, there is no statistically significant nonlinear structure arising from the ‘smart’ money channel for any of the returns. To highlight the nonlinear structure in the returns of HEX, Forest and Telecom & Electronics, the estimated mean impact curves of these three portfolios are presented in Figure 15.

In computing the MICs, the conditional mean \(\mu_{t,t-1}\) and conditional variance \(\sigma^2_{t,t-1}\) used in the formulae in Equations (37) and (38) are replaced by their respective sample averages. All three MIC graphs display similar qualitative structures to the stylized MIC shape of MIC-1 presented in Figure 1. The MIC graphs exhibit a positive relationship between the conditional mean and news around \(\epsilon_{t,t-1} = 0\), suggesting that these returns exhibit mean aversion for relatively ‘small’ shocks. For relatively larger shocks, the MIC graphs turn back on themselves resulting in mean reversion in returns with large positive (negative) shocks now having a negative (positive) effect on average returns of these portfolios. The results for Other Service,

\(^{20}\) The assumption of the disturbances being normally distributed is also relaxed by computing quasi maximum likelihood standard errors of Bollerslev and Wooldridge (1992). This revealed no qualitative changes in the results of the trading model.
Figure 15: Mean impact curve of the HEX, the Telecom and Electronics, and the Forest index based on the GJR (1, 1) conditional variance: The mean impact curve contains all three trading channels and the equation for the curve is

\[
\mu_{i,t} = \begin{cases} 
  a_{i,0}^+ + a_{i,1}^+ \varepsilon_{i,t-1}^+ + a_{i,2}^+ \varepsilon_{i,t-1}^+ + a_{i,3}^+ \varepsilon_{i,t-1}^+ : & \varepsilon_{i,t-1} < 0 \\
  a_{i,0}^- + a_{i,1}^- \varepsilon_{i,t-1}^- + a_{i,2}^- \varepsilon_{i,t-1}^- + a_{i,3}^- \varepsilon_{i,t-1}^- : & \varepsilon_{i,t-1} \geq 0
\end{cases}
\]

where \( a_{i,0}^+ = \gamma_1 + \lambda \alpha + (\gamma_2 + \gamma_3 \alpha) \mu_{i,t-1} + (\lambda + \gamma_1 \mu_{i,t-1}) \beta \sigma_{i,t-1}^2 \). The term \( \mu_{i,t} \) is the expected return at time \( t \) and \( \varepsilon_{i,t-1} \) is the unpredictable return at time \( t-1 \). The term \( \alpha_{i,t}^+ = \gamma_1 + \gamma_2 \alpha + \gamma_3 \alpha \mu_{i,t-1} \) where the parameter \( \gamma_1 \) corresponds to nonsynchronous trading. \( \gamma_2 \) represents positive feedback trading. The parameter \( \gamma_3 \) measures the risk free rates of return. The term \( \alpha_{i,t}^- = \lambda (\alpha + \varphi + (\gamma_2 \alpha + \gamma_3 \varphi) \mu_{i,t-1} \) and \( \alpha_{i,t}^- = \alpha_1 (\lambda + \gamma_2 \mu_{i,t-1}) \), where \( \lambda \) measures the risk premium. The parameters \( \alpha_0, \alpha_i, \) and \( \beta_i \) are in the GJR (1, 1) variance process. The term \( \alpha_{i,t}^- = \gamma_1 (\alpha + \varphi) \) and \( \alpha_{i,t}^- = \gamma_2 \alpha_1 \) where \( \varphi \) captures the leverage effect. The shape of the above mean impact curves is indicative of cases with parameter values obtained from the maximum likelihood estimates of the feedback trading model.
Telecom & Electronics and Metal & Engineering in Table 10, while revealing no evidence of nonlinearities, the p-values of $\gamma_i$ for these assets, do nonetheless represent significant linear structures in the mean arising from nonsynchronous trading. By contrast, Bank & Finance, Other Industry, Trade and Food, reveal no evidence of any structure in returns as all the key trading parameters $(\gamma_1, \lambda, \gamma_3)$ are found to be statistically insignificant. In the case of Bank & Finance, this result is consistent with the previous empirical results of Östermark, Aaltonen, Saxén and Söderlund (2004)\textsuperscript{21}.

A consistent empirical result across all assets is that the reported p-values of the risk-return trade-off parameter $\lambda$, shows that there is no significant trading channel arising from smart money. This result is consistent with Sentana and Wadhwani (1992) and Koutmos (1997), who find no strong evidence of smart money trading strategies, once this channel is nested within a more general trading model.

Another significant empirical result that is consistent across all asset returns is that the conditional variance exhibits a significant asymmetry with the estimates of the asymmetry parameter $\varphi$, occurring in the range of 0.034 for Telecom & Electronics to 0.165 for Metal & Engineering. From the discussion of Figure 4, a positive estimate of the asymmetry parameter has the effect of rotating the MIC upwards for negative values of the news. This result implies that large negative shocks in general have a much bigger (positive) impact on average returns than do large positive shocks.

\textsuperscript{21} The lack of any significant evidence of a nonlinear MIC schedule is not too surprising for Other Industry, given that returns on this portfolio revealed no evidence of autocorrelation at any lags. However, as Bank & Finance and Food were found to exhibit significant autocorrelation in returns at higher lags in Table 3, an extension of the empirical model at least for these two portfolios would be to re-estimate the model using longer lags to identify the MIC.
Diagnostic tests of the trading model for the HEX and its components based on the standardized residuals \( z_t \), are given in Table 11. The first two tests reported show that the null hypothesis that \( z_t \), has zero mean and unit variance cannot be rejected at the usual significance levels. The Ljung-Box tests of autocorrelation reveal no autocorrelation in the levels or squares of \( z_t \). The MIC joint test reveals no nonlinear structure in the standardized residuals, while the joint NIC test reveals no nonlinear structure in the variance. The most statistically significant result is the sign bias test of the HEX, where it is just statistically significant at the 5% level, but not at the 1% level.
Chapter 8
Concluding remarks

This paper has introduced a new framework called the mean impact curve to identify nonlinearities in stock returns. The mean impact curve maps the relationship between the conditional mean of returns and the news. In the case of the heterogeneous investor trading model developed in the thesis, the mean impact curve is represented as a cubic equation in the news factor. To complete the specification of the trading model, it is necessary to specify the form of the conditional volatility.

A range of diagnostic tests like LB test statistic, sign bias, negative size bias, positive size bias and joint tests are used to find the nature of the ARCH effect. All these tests reject the independence for the entire squared return index series. The values of LB statistic are on average greater for the squared return series than the values of LB statistic for returns, indicating that nonlinear time dependencies are much stronger than linear time dependencies. The presence of the ARCH effect is inconsistent with the random walk model but does not violate the Martingale process. The market efficiency theory is based on the Martingale theorem. Thus, the departure from the pure random walk does not, however, violate the efficient market hypothesis.

Standard GARCH along with EGARCH, GJR and WGARCH are compared to find the best fitted volatility model, depending upon the news impact curve. The news impact curve is symmetric in GARCH but EGARCH and GJR capture the leverage or asymmetric effect by allowing a different slope of the two sides of the news impact curve in each index. The asymmetry in information releases is not common among different industries according to WGARCH estimates. Thursdays’ news decrease volatility in Bank and Finance, Forest, Telecom and Electronics and in
Table 11

Diagnostic tests of the feedback trading model for the HEX and the industry sorted portfolios: p-values reported in square brackets.

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<tr>
<th>Coefficients</th>
<th>Bank Finance</th>
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<th>Metal &amp; Engineering</th>
<th>Forest</th>
<th>Other Industry</th>
<th>Telec &amp; Electronics</th>
<th>Trade</th>
<th>Food</th>
<th>HEX</th>
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<td>-0.278</td>
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<td>0.008</td>
<td>-0.013</td>
<td>-0.071</td>
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<td>[0.998]</td>
<td>[0.982]</td>
<td>[0.972]</td>
<td>[0.874]</td>
<td>[0.908]</td>
<td>[0.994]</td>
<td>[0.989]</td>
<td>[0.943]</td>
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<td>8.032</td>
<td>3.830</td>
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<td>5.319</td>
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<td>[0.802]</td>
<td>[0.643]</td>
<td>[0.910]</td>
<td>[0.661]</td>
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<td>3.600</td>
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<td>0.169</td>
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<td>1.130</td>
<td>-0.583</td>
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<td>[0.389]</td>
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<td>[0.737]</td>
<td>[0.259]</td>
<td>[0.560]</td>
<td>[0.646]</td>
<td>[0.049]</td>
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<td>-1.456</td>
<td>-1.813</td>
</tr>
<tr>
<td>P-value</td>
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<td>[0.460]</td>
<td>[0.576]</td>
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<td>1.236</td>
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<td>0.972</td>
<td>1.652</td>
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<td>[0.295]</td>
<td>[0.124]</td>
<td>[0.942]</td>
<td>[0.405]</td>
<td>[0.175]</td>
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</table>
HEX, but in Food and Trade, Thursdays’ news increases volatility on Fridays. Fridays’ news is significant only in Food and HEX. This evidence suggests that information released by corporate and institutional authorities on Fridays has little impact on the Finnish stock market. Furthermore, Fridays’ news decreases market volatility less than Thursdays’ news.

The steepness of the news impact curve is used as a measure of news sensitivity in this research. The steeper the news impact curve the higher the news sensitivity. Metal and Engineering has the highest and Telecom and Electronics has the lowest news sensitivity in the Finnish stock market according to GARCH, EGARCH and GJR estimates. This evidence also holds for WGARCH, considering Otherdays’ news. Thursdays’ news has the highest impact in decreasing the volatility of Fridays in Telecom and Electronics according to WGARCH estimates. In this industry, Fridays’ news impact curve is horizontal. This means that Thursdays’ news fully compensate the Otherdays’ news. In other words, news from Thursdays decrease the same amount of volatility as is increased by news from Otherdays. Most importantly, the different specification tests are performed on the standardized residuals including sign bias, negative size bias, positive size bias and joint tests, to select the best fitted volatility model. The chosen model seems to be the one proposed by Glosten, Jagannathan, and Runkle (GJR) in comparison to GARCH, EGARCH and WGARCH models according to these tests.

To highlight the relationship between the conditional mean and the news, start with the simplest representation of volatility given by the ARCH model, the GARCH and lastly by the GJR model. The mean impact curve is shown to exhibit a range of shapes depending upon the importance of ‘smart’ money traders, feedback traders including traders who adopt contrarian trading strategies, and nonsynchronous trading arising from thinly traded markets.
A set of diagnostic tests has also been developed to provide a preliminary test of any nonlinearities in the data. The mean impact curve is applied to identify nonlinearities on stock returns in the Helsinki Stock Exchange (HEX) and many of its components. Significant nonlinearities are detected in the HEX and Forest, as well as in Telecom & Electronics. Other Service and Metal & Engineering reveal evidence of positive autocorrelation in mean returns, but no evidence of nonlinearities. No evidence of any structure in the conditional mean of returns of Bank & Finance, Trade, Food and Other Industry is detected.

An important advantage of the mean impact curve is that it can be used to reconcile differences in earlier empirical results that have identified mean reversion in stock returns in some cases and mean aversion in other cases. For example, a typical mean impact curve arising from the empirical analysis shows that for relatively ‘small’ shocks there is mean aversion with returns adjusting positively (negatively) to positive (negative) shocks. For relatively ‘large’ shocks however, there is evidence of mean reversion with positive (negative) shocks now having a negative (positive) effect on returns. Moreover, as there is evidence of significant asymmetries in the conditional variance, the effects of negative shocks tend to have a greater impact on average returns than a positive shock of comparable magnitude. In the context of the trading model that is used to motivate the structure of the mean impact curve, this suggests that, whilst nonsynchronous trading tended to result in returns being positively correlated, extreme movements in the returns of assets could eventually mean revert, provided that part of these movements are accounted for by positive feedback trading (DeBondt and Thaler (1985)).

Furthermore, it is possible to develop the mean impact curve analysis by improving the procedure of estimation of the feedback trading model. The maximum likelihood estimates of the
feedback trading model, where returns are assumed to be normally distributed, may be biased. One could follow the procedure developed by Andreev, Kanto and Malo (2007) to find the correct distribution of stock returns. Even if the assumption of conditional normality is incorrect, as long as the conditional means and variances are correctly specified, the maximum likelihood estimates will be consistent and asymptotically normal, as pointed out by Bollerslev and Wooldridge (1992).
Bibliography


Appendix A

Appendix A presents the maximum likelihood estimates of various predictable volatility models, using daily logarithmic rates of return from the Helsinki stock exchange for the period of 2nd January 1997 to 30th December 2003. The estimation is performed by using the BHHH numerical optimization algorithm. The univariate representation of the GARCH (1, 1) model

\[ R_{t,i} = \gamma_i + \gamma_i R_{t,i-1} + \epsilon_{t,i}; \epsilon_{t,i} = \sqrt{\sigma^2_{t,i}}, \text{ where } z_{t,i} \sim \text{i.i.d. } N(0,1) \]

\[ \sigma^2_{t,i} = \alpha_0 + \alpha_1 \epsilon^2_{t,i-1} + \beta_1 \sigma^2_{t,i-1}. \]

The univariate representation of the EGARCH (1, 1) model

\[ \sigma^2_{t,i} = \exp\left(\alpha_0 + \alpha_1 f(z_{t,i-1}) + \beta_1 \ln(\sigma^2_{t,i-1})\right) \text{ and } f(z_{t,i}) = |z_{t,i}| - E(|z_{t,i}|) + \varphi z_{t,i}. \]

The univariate representation of the GJR (1, 1) model

\[ \sigma^2_{t,i} = \alpha_0 + \alpha_1 \epsilon^2_{t,i-1} + \varphi S_{t,i-1} \epsilon^2_{t,i-1} + \beta_1 \sigma^2_{t,i-1}. \]

The univariate representation of the WGARCH (1, 1) model

\[ \sigma^2_{t,i} = \alpha_0 + \alpha_1 \epsilon^2_{t,i-1} + \varphi S^{+}_{t,i} \epsilon^2_{t,i-1} + \varphi_2 S^{-}_{t,i} \epsilon^2_{t,i-1} + \beta_1 \sigma^2_{t,i-1}. \]

The term \( R_{t,i} \) represents the daily logarithmic rates of return of the HEX and the industry-sorted portfolios. The term \( \epsilon_{t,i} \) is the unpredictable return at time \( t \), \( z_{t,i} \) is the standardized residual at time \( t \), \( \sigma^2_{t,i} \) is the conditional variance at time \( t \). The term \( \gamma_i R_{t,i-1} \) allows for possible autocorrelation due to nonsynchronous trading of the stocks that make up the index. The parameters \( 0 \leq \alpha_0 < 1, \ 0 \leq \alpha < 1, \ 0 \leq \beta < 1 \) are constant in the various predictable volatility models. Most importantly, the parameter \( \varphi \) captures the leverage effect. The effects of Fridays’ and Thursdays’ news are captured by the parameters \( \varphi_1 \) and \( \varphi_2 \), respectively. Ljung-Box (n) is the Ljung-Box (LB) test statistics for \( n^{th} \) order autocorrelation of standardized residuals.
### Appendix A – Continued

Industry-sorted Portfolios and The HEX index

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<td>WGARCH</td>
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### Appendix A – Continued

Industry-sorted Portfolios and The HEX index

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## Industry-sorted Portfolios and The HEX index

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## Appendix A – Continued

### Industry-sorted Portfolios and The HEX index

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Mean of $z_{jt}$

Variance of $z_{jt}$

Ljung-Box (5) for levels

Ljung-Box (10) for levels

Ljung-Box (5) for squares

Ljung-Box (10) for squares

P-value

Mean of $z_{jt}$

Variance of $z_{jt}$

Ljung-Box (5) for levels

Ljung-Box (10) for levels

Ljung-Box (5) for squares

Ljung-Box (10) for squares

P-value
### Appendix A – Continued

#### Industry-sorted Portfolios and The HEX index

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#### Mean of \( z_{it} \)

-0.031  -0.020  -0.007  -0.031  -0.032  -0.037  -0.023  -0.032

#### Variance of \( z_{it} \)

0.999  1.054  0.999  0.998  0.994  1.024  0.995  0.994

#### Ljung-Box (5) for levels


#### Ljung-Box (10) for levels

5.785  0.577  0.667  0.634  0.927  0.905  0.910  0.930

#### Ljung-Box (5) for squares


#### Ljung-Box (10) for squares


#### P-value

[0.049]  [0.385]  [0.880]  [0.388]
Appendix B

Appendix B shows the news impact curves of the GARCH (1, 1) model, the EGARCH (1, 1) model and the GJR (1, 1) model for each industry index. The solid line is the GARCH (1, 1) news impact curve. The dark dashed line is the EGARCH (1, 1) news impact curve. The light dashed line is the GJR (1, 1) news impact curve. The intercept term of the news impact curve is assumed to be fixed for each model to draw these curves.
Appendix B – Continued

![Diagram showing news impact curves for Other Industry and Telecom and Electronics industries.](image)

- EGARCH news impact curve
- GARCH news impact curve
- GJR news impact curve

![Diagram showing news impact curves for Other Industry and Telecom and Electronics industries.](image)

- GJR news impact curve
- GARCH news impact curve
- EGARCH news impact curve
Appendix C

Appendix C reports the Otherdays’ news impact curve, Mondays’ news impact curve and Fridays’ news impact curve of the WGARCH (1, 1) model for each industry index. The solid line is the Otherdays’ news impact curve. The light dashed line is the Mondays’ news impact curve. The dark dashed line is the Fridays’ news impact curve.
Appendix C - Continued

![Graph showing impact curves for Forest and Telecom and Electronics](image)

- Forest
  - Otherdays’ news impact curve
  - Fridays’ news impact curve

- Telecom and Electronics
  - Fridays’ news impact curve
  - Otherdays’ news impact curve
Appendix C - Continued

\[ \sigma_{ij}^2 \]

\[ \varepsilon_{s,t-1} \]

Trade

\[ \sigma_{ij}^2 \]

\[ \varepsilon_{s,t-1} \]

Food

Fridays' news impact curve

Otherdays' news impact curve

Mondays' news impact curve

Fridays' news impact curve

Otherdays' news impact curve