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IDENTIFICATION OF INVESTMENT STRATEGIES AND RISK PREMIUM IN STOCK EXCHANGES

of

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Abstract

Efficient market hypothesis (hereafter, EMH) has been widely discussed for over thirty years or so however it failed to explain various economic events observed in world financial markets. Therefore, Behavioural Finance goes beyond the limitations of the forementioned theory and with the use mainly of cognitive psychology, attempts to explain heterogeneous investor reactions and their consequences in real equity markets.

There can be no doubt that some investors try to unveil trends in past stock prices and base their portfolio decisions on the expectation that these trends will remain constant throughout time. These investors are often found in literature as 'feedback traders'. Yet, they exhibit positive feedback trading behaviour when they 'buy low and sell high' creating a particular pattern in the market and driving prices away from fundamentals. Following that, they formulate price bubbles, market crashes and high return volatility of asset prices is being observed.

The aim of this study is to examine the trading strategies that lie behind the interactions of agents in two major U.S. indices – the Dow Jones and S&P 500. The research is conducted using daily stock prices from 02/01/1957 to 22/12/2001. The relevant time series are all examined for unit root using the Augmented Dickey-Fuller (1979) test while heteroscedasticity is appropriately taken into account with the use of a (G)ARCH-M model. For the first time, we implement a newly developed model, called – GARCH-M-MG by providing two fundamental variables; the risk premium and feedback trading captured under the non-linear dynamics of the model. Since the studied period is too long, we chose to subdivide it into two parts, with the break-even point dated back to 10/03/2000 when the Dot-Com bubble burst.

Our findings reveal the following:

- negative sign of risk premium that is mainly attributed to various 'anomalies' detected in the 3-month treasury bill determination. Normally we should expect a positive sign (according to the theory).
- Even if positive feedback is evident and statistically significant, it does not affect the behaviour of risk premium.

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Introduction

Long ago, the Efficient Market Hypothesis (hereafter, EMH) was widely accepted by academic financial economists. It was generally believed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. Specifically, when new information is introduced into the market it is being absorbed into the price of securities without any additional delay. The EMH was primarily associated with the idea of 'random walk' - a term widely used in finance literature to characterize a price series where all subsequent prices represent random departures from their lagged values.

Nonetheless, further empirical studies (Poterba and Summers (1988), Lo and Mackinlay (1988)) suggested that there is little evidence to the trend of stock prices is similar to a random walk process. There seems to be an inherent 'power' that drives investor sentiment to a proper direction and make prices diverge away from their fundamental values. As a result, high volatility and excess returns are observed while intense speculative phenomena (bubbles and crashes) are being deployed into various financial systems.

As agents do not process information as supposed to, a high degree of heterogeneity is being detected, so their individual behavioural characteristics make them irrational in an attempt to determine the 'best-fit' strategy. On top of that, they create 'noise' in the market, by making the system more unstable and provoke complex dynamics in the formulation of their portfolio decisions.

Furthermore, one of the consequences of the existence of the forementioned heterogeneous agents is the autocorrelation of returns and the partial predictability of aggregate stock returns. Positive feedback trading strategies – i.e. 'buying past winners and selling past losers', are empirically examined that proved to govern today's financial markets.

In contrast, the exercise of the appropriate monetary policy from central banks, plays also a significant role in driving stock prices to the right direction since their objective is to maintain financial stability in world equities markets. Under this assumption, for the past 10 or 15 years, the most common policy was of setting short-term interest rates with the primary aim of targeting inflation and controlling any macroeconomic conditions in respect (Driffill *et al.*, 2006).

With the passage of time and the growth in the sophistication of financial markets, the period from 2000 to nearly 2007 was one of low interest rates, arising from significantly high levels of liquidity as many developed countries attempted to keep up their current account surpluses and exchange rate levels. As a result, short-term interest rates were pushed downwards and long-term ones were even further suppressed. Consequently, asset price bubbles were created and preceded the world financial crisis (Barrell and Davis, 2008).

Having taken all the forementioned into account, the aim of this study is to examine the effects of risk premium and feedback trading on the excess returns of two major U.S. stock indices; the Dow Jones and S&P 500 from 1957 to 2011.

The corresponding empirical examination is based upon the identification of the unit root in the dataset (Augmented Dickey-Fuller testing) and a further investigation with the use of GARCH-M (Generalized Autoregressive Conditional Heteroscedasticity in Mean) model is utilized so as to remove any heteroscedasticity implications in the sample. Descriptive statistics are being thoroughly reported and finally a newly developed model named GARCH-M-MG (Generalized Autoregressive Conditional Heteroscedasticity in Mean with a univariate noisy Mackey-Glass factor) is being used is defining the exact relationship of risk-premium and feedback trading and further evidence are provided.

The remainder of the project is organized as follows; Chapter 2 includes a broad literature review on the efficient market hypothesis, on the concept of 'heterogeneity' in financial markets and on the various heterogeneous agent models, as well as a brief discussion is implemented with regards to positive feedback trading effects. Chapter 3 entails all the empirical findings from the research and an extensive analysis is provided. Finally, at the end of Chapter 3 a detailed discussion summarizes the main results and concludes the project, by pointing out the limitations of the study and offering further recommendations for future research.

Chapter 1 – Literature Review

This chapter is divided into three main parts that constitute the basic theoretical framework of this research thesis.

In the first part, it is going to be presented a brief review of the Efficient Market Theory, or else the Efficient Market Hypothesis (hereafter EMH) and its theoretical and empirical implications that were developed throughout years and research. The basic notion of "market efficiency" will be discussed with an extensive reference to the main inefficiencies of EMH that answer the question "Do the markets actually behave efficiently?"

Following that, the second part will be devoted to the concept of "heterogeneity of investors", that is of prime importance, as an immediate drawback of capital markets and one of their characteristics. Some significant models of heterogeneous agents will be reported as well as their empirical findings.

Finally, the third part will deal with the basic feedback mechanisms of traders' behaviour, which can either be positive or negative. The literature behind the idea of "feedback trading" is basically attributed to the heterogeneity of the interacting agents and their investment choices, as they tend to form specific strategies in order to maximize their wealth.

1.1. Efficient Market Hypothesis – A review

No concept in investment finance has ever been widely tested and severely judged as the "market efficiency". Yet it provides the basic quantitative framework for modern financial economics for the past 50-plus years and the development of Behavioural Finance (hereafter BF).

The original work dates back to 1900s when a prominent French mathematician, Louis Bachelier[1], firstly introduced the view of *random walk.* According to that, security prices move independently of each other, i.e. today's price cannot be associated with yesterday's price of an asset, thus Fama's rational investors form their decisions following that rule. Mathematically this can be expressed as:

$$P_t = P_{t-1} + e_t$$

[1] Bachelier, L., 1900, "Theorie de la speculation", Gauthiers-Villars.

where P_t and P_{t-1} are denoting the price of an asset at time t and t-1 respectively and e_t represents a random variable, or 'white noise' following the normal distribution [$e_t \sim N(0,1,)$].

Meanwhile, around 1950s and after an extensive research on capital market theories throughout years, Harry Markowitz (1952) in his published paper "Portfolio Selection" developed the so-called *Modern Portfolio Theory,* alternatively the Portfolio Optimization Approach. The theory attempted to describe a way in which investors experience high expected returns, at a given level of risk. Its main assumptions are summarized below (Reilly and Brown, 2003, p. 211):

1) *All investors aim to maximize economic utility,*
2) *All investors are rational and risk-averse,*
3) *All investors have access to the same information at the same time,*
4) *There are no taxes or transaction costs,*
5) *Investors consider each investment alternative as being represented by a probability distribution of expected returns over some holding period.*
6) *Investors estimate the risk of the portfolio on the basis of the variability of expected returns.*
7) *Investors base decisions solely on expected return and risk, so their utility curves are a function of expected return and the expected variance (or standard deviation) of returns only.*
8) *For a given risk level, investors prefer higher returns to lower returns. Similarly, for a given level of expected return, investors prefer less risk to more risk.*

Markowitz, through the construction of the efficient frontier, proposed a measure of riskiness of the portfolio using the population variance as stated below:

$$\sigma^2 = \sum_{i=1}^{\infty} (r_i - r_\mu)^2$$

where, σ^2 = variance

r_μ = mean return

r_i = mean observation

Therefore investors would wish for a portfolio with a highest expected return for a level of a given risk, thus they are willing to accept a higher level of risk only if they are compensated by higher expected earnings, assuming that they are risk-averse and rational.

Moreover, the theory models a situation where an asset's return is normally distributed (Gaussian distribution), with the risk as mentioned before (σ^2) and projects a diversified portfolio of weighted combinations of different assets that are positively correlated:

$$R_x = W_A R_A + W_B R_B,$$

where A and B the different assets, R_A and R_B are their corresponding return values, W_A and W_B their weights and R_x the return of the portfolio of two assets.

Therefore, an investor can diversify away risk by choosing among different types of assets and eliminating initially the non-systematic risk[2], let alone the systematic[3]. At this point it would be worthwhile to mention that *beta (β)* coefficient is defined as a measure of systematic risk and mathematically is expressed as:

$$\beta_\iota = \frac{Cov_{iM}}{\sigma^2_{\mathrm{M}}}$$

where Cov_{iM} is the covariance of an asset with the market portfolio *M* and σ^2_{M} is the variance of the market return. The higher the beta coefficient the more aggressive is considered to be the portfolio and vice versa. Intuitively one could assume that finance managers structure their investment decisions solely on the risk measure, not taking into account the fundamental values of the assets by creating 'expensive' portfolios for the investors since they do not take the fundamental values of the assets into account.

As all the above describe an optimal behaviour of an individual investor, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1963), Lintner (1965) and Mossin (1966) came in to supplement the actual pricing of assets, combining the central points of Markowitz's portfolio theory into a model of investor behaviour based on rational expectations in a general equilibrium framework, expressed as,

$$\overline{R_i} = R_F + \beta(R_M + R_F)$$

where $\overline{R_i}$ is the mean return on an asset i, R_F the risk-free rate, β the beta coefficient and R_M the return of the market.

Since the CAPM has been extensively discussed in the literature, our main reason of reference is purely informational in the sense that its underlying assumptions are pretty much the same governing the main idea of this review – the efficient market hypothesis.

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[2] Non-systematic risk is the risk that is unique to each individual asset and is diversified in a portfolio.
[3] Systematic risk is the risk that is derived from the market and is influenced by various macroeconomic and financial variables.

Summarizing the above, the initial capital market theories were mainly devoted upon 'rationality' and 'random walks', under the assumptions of normality but not until 1970s when Fama (1970) introduced to the financial community the concept of **'efficiency in markets'**.

He defined an efficient financial market as '*one in which security prices always reflect the available information*' and '*prices adjust to new levels corresponding to the new net present values of cash flows*' (*informational efficient market hypothesis*) (pp. 383). His key hypotheses were:

1) There are no transaction costs,
2) All investors are homogeneous and rational (they make no mistakes, the do not mimic, they adjust their investment decision according to the trends of the market and they have full access to any given information)
3) There are not systematic mechanisms making prices deviate from fundamentals but only news or shocks that cannot be predicted,
4) All information in correct and mirrored instantly in prices.

Additionally, Beechey, Gruen and Vickery (2000), in their research paper summarized all the above, hence for the reader's comfort, we provide the table below.

Predictions of the Efficient Market Hypothesis

Prediction	Empirical Evidence
Asset prices move as random walks over time.	Approximately true. However: Small positive autocorrelation for short-horizon (daily, weekly and monthly) stock returns. Fragile evidence of mean reversion in stock prices at long horizons (3–5 years).
New information is rapidly incorporated into asset prices, and currently available information cannot be used to predict future excess returns.	New information is usually incorporated rapidly into asset prices, although there are some exceptions. On current information: In the stockmarket, shares with high returns continue to produce high returns in the short run (*momentum effects*). In the long run, shares with low price-earnings ratios, high book-to-market-value ratios, and other measures of 'value' outperform the market (*value effects*). In the foreign exchange market, the current forward rate helps to predict excess returns because it is a biased predictor of the future exchange rate.
Technical analysis should provide no useful information	Technical analysis is in widespread use in financial markets. Mixed evidence about whether it generates excess returns.
Fund managers cannot systematically outperform the market.	Approximately true. Some evidence that fund managers systematically underperform the market.
Asset prices remain at levels consistent with economic fundamentals; that is, they are not misaligned.	At times, asset prices appear to be significantly misaligned, for extended periods.

Source: Beechey, Gruen and Vickery (2000)

Mathematically, suppose that at any point in time all the available information that exists at the disposal of investors is denoted as Ω_t and market participants as *p*. Their information set is being constructed as Ω_t^p and is assumed to be costless. In an efficient market where all agents are well-informed, the probabilistic density function for returns comes as,

$$f^p(R_{t+n} | \Omega_t^p) = f(R_{t+n} | \Omega_t).$$

Hence, in that market, investors are informed about the real economic model that generates future returns and make use of all available information to form their best-fitted forecasts (Cuthbertson, 1996).

Furthermore, in his original paper, Fama (1970, 1991) divided the overall EMH into three subcategories depending on the information set involved: *the weak-form EMH, the semi-strong form EMH and the strong-form EMH.*

The weak-form EMH

It assumes that the only relevant information used in order to determine current security prices is the *historical prices* of that particular security. In this regard, past rates of return cannot guarantee future rates of return, therefore price movements occur randomly and successive price changes are independent of each other (random walk hypothesis).

Empirically one could test this form of efficiency using two measures; a.) the well-known statistical tests of independence (autocorrelation tests, runs tests) and b.) trading-rule tests.

The semi-strong form EMH

The second form of efficiency asserts that *all public information* in being reflected in stock prices, therefore market can move prices to a new equilibrium level that reflects the changes in supply and demand caused by the introduction of news. It encompasses all the main characteristics of the weak-form, implying that investors should base their decisions on information that is prior publicly driven and they should not expect above-average returns, as “everybody else knows”. Nevertheless, this form of efficiency is supposed to be stronger than the weak-form with regards to the assumption that it requires market analysts having the skills, ability and knowledge in order to form their investment strategies.

Tests that have been used in order to examine this form of efficiency include time-series analysis, cross-sectional distribution analysis and event-studies analysis reassuring how fact stock prices respond to exogenous economic events.

The strong-form EMH

Finally, the strong-form of efficiency implies that stock prices fully reflect *all public and private information*. It combines both the weak-form and semi-strong form of EMH, suggesting that no investor has a monopolistic interest on any information available. Until information has fully been absorbed into stock prices, investors will keep buying stocks and driving prices up. Since there will be no incentive to invest more, they will withdraw from the market, bringing the price to a new equilibrium level.

As Dima and Milos (2009) point out, identifying the right form of efficiency is not an easy task. It involves sophisticated econometric methods and cautious choice of the proper information set that is going to be tested, however it is a very useful process in order to justify excess returns obtained beyond the risk of the agents.

1.1.1. Limitations of the Efficient Market Hypothesis

1.1.1.1. – General Empirical Findings

The findings from the empirical testing of the EMH ended up to be mixed and controversial. Early studies conducted by Fama (1965) and Samuelson (1965) did not reject the random walk hypothesis in contrast to Niederhoffer and Osbourne (1966) who found that after a non-uniform distribution of orders, non-random effects in stock prices are being produced. Shiller (1989) supports also that stock prices express random behaviour.

Additionally, Poterba and Summers (1988) as well as Lo and Mackinlay (1988) argue that the trend of stock prices is similar to a random walk process. Specifically, Lo and MacKinlay (1988) used weekly data from 1216 observations dating back from September 1962 to December 1985. They estimated the first-order autocorrelation coefficient of the equal-weighted Center for Research in Security Prices (CRSP) index and concluded that their hypotheses did not conform to the stochastic behaviour of weekly returns, i.e. stock prices are not randomly distributed.

Timmermann and Granger (2004) provide an extensive research on the weak points of the EMH by presenting various forecasting techniques, arguing that stock prices movements might end up in creating patterns due to the stationarity (or even non-stationarity) effects in time series. They also point out that transaction costs as well as trading restrictions play a significant role in addressing a profitable investment strategy in a sense that high transaction costs deter agents from investing in predictable events in the short-run (e.g. a particular equity might outperform market next year by 2% and the costs associated with this action are 3%), a view that was supported as well by Shleifer and Vishny (1990). In addition, if short-selling cannot be realized, certain types of asymmetric predictability are not consistent with EMH because they cannot be thought of as a profitable trading strategy. Finally, they comment on the uncertainty about model specification indicating the investors face difficulty in choosing the best-fit model so as to predict market efficiency.

Furthermore, McGoun (1990) after having tested the three forms of efficiency (weak-form, semi-strong form and strong-form) finds that the weak-form is a non-testable concept whereas the strong-form is true by definition. Thus, the subsets of information contained in the studied forms of EMH cannot arguably explain market efficiency.

Moving forward, literature suggests that there are some patterns of price predictability such as those suggested by Lo and MacKinlay (1999). They found out that short-run serial correlations are not zero and prices move to the same direction at the same time. They rejected the hypothesis that equity prices follow a random walk and mentioned that they express a kind of short-run momentum. Investors are driven into the market in a kind of ‘bandwagon effect’. Malkiel (2003), reports that behaviouralists see short-run momentum as a tendency for agents to underreact to new information, indicating that psychological feedback mechanisms are apparent. In contrast, Fama (1998) who stretches out that, underreaction to new information is as common as overreaction to the same information and this problem can be confronted by using different methods to adjust risk and return.

Another empirical issue to be discussed further is the one that deals with long-run reversals, i.e. negative serial correlation in returns, which is being attributed to the overreaction of agents. DeBondt and Thaler (1985) used monthly data for New York Stock Exchange (NYSE) common stocks as compiled by CRSP for the period of January 1926 to December 1982 and concluded that individuals tend to overreact to unexpected and unpleasant news. Portfolios of prior losers were found to be performing better than prior winners. In fact, Poterba and Summers (1988) and Lehmann (1990) also came to the same conclusion – mean reversion occurs at longer horizons.

Shleifer and Summers (1990) provide an extensive work on an alternative view of market efficiency that is being based on investor sentiment and limited arbitrage. They conclude that limited arbitrage and not perfect arbitrage as market efficiency implies, drives investor sentiment closer in determining equity prices.

Finally, an important issue to be addressed at this point is the one that deals with 'herd behaviour' and its consequences. Herding is defined as: 'when people take the same action, because some mimic the actions of others' and is usually observed to similar behaviour in animal groups (Sornette, 2003, p. 94). Lux, (1995) in his research paper, provides an extensive review of herding and how it leads to bubbles and crashes, justifying the fact that markets are far from efficient. Initially he introduces the notion of 'contagion' and claims the view that an investor is willing to buy an asset if he sees others buying it too. The reason behind this is that others' movements may give the impression that better and more information are apparent thus influencing investors' point of view. He then continues by constructing a model where he tests the degree of contagion within the different sets of investors (optimistic and pessimistic ones).

The optimistic investors are denoted as n_+ and the pessimistic as n_- and a fixed number of *2N* speculative traders exists. Following that, the probabilities (p) for an optimistic trader to become pessimistic and *vice versa* are depicted below:

$$p_{-+} = p_{-+}(x) = p_{-+}(n/N), \qquad p_{+-} = p_{+-}(x) = p_{+-}(n/N) \qquad (1)$$

He comments that first, all transition probabilities have to be positive by definition and second if the population is characterized as optimistic, the probability of transition from pessimistic to optimistic is larger than the opposite direction and *vice versa*. The assumptions lead to the following functional forms of herding, commonly used in literature:

$$p_{+-}(x) = ve^{ax}, \qquad p_{-+}(x) = ve^{-ax} \qquad (2)$$

Here *a* is indicated as herd behaviour and *v (velocity)* is a variable for the speed of change of attitudes. Additionally the time development for the index *x* is calculated as:

$$dx/dt = (1-x)ve^{ax} - (1+x)ve^{-ax} = 2v\left[Sin(ax) - xCos(ax)\right]$$

$$= 2v\left[Tan(ax) - x\right]Cos(ax) \qquad (3)$$

Furthermore, he provides the subsequent proposition (I): *i.) For a ≤ 1, eq. (3) possesses a unique stable equilibrium at x=0, ii.) For a > 1, the equilibrium x=0 is unstable and two additional, stable equilibria say* $x_+ > 0$, $x\_ < 0$ *exist* ($x_+ = -x_-$). According to that if the herd effect is weak then any movement in the same direction will phase out and the system will return to its steady-state equilibrium after some disturbance. However, if a > 1 and contagion of effects is apparent, then some minor departures from the steady-state will bring about bullish or bearish traders, creating a bubble. In addition, any departures from the equilibrium condition x = 0, create unstable situations where price dynamics move like a 'snowball' and end up either in an optimistic or pessimistic position.

On the other hand, he proposes the view of considering endogeneous mechanisms that generate reversals of traders' behaviour. He then develops a model where two different market agents participate. Namely, *the speculators* with net excess demand:

$$D_N = n_+ t_N - n\_ t_N = 2nt_N$$

where t_N represents a fixed amount of stock that traders are willing to sell or buy and *the fundamentalists*, with net excess demand:

$$D_F = T_F (p_f - p), \qquad T_F > 0$$

Any interactions between them (either selling or buying stocks) create feedback mechanisms that generate bubbles and even crashes, hence both excess volatility and mean-reversion phenomena are being utilized. Lux (1995) claims that speculative traders tend to behave irrationally, are being drawn upon easily and induce small investors to engage in the feedback process by destabilizing the market. He also comments that, considering the above into a dynamic structure, then fat tails (leptokurtosis) are being observed.

Alternatively, Lakonishok *et al.*, (1992) provide a similar study on herding with regards to institutional trading. They used end-of-portfolio holdings from 769 all-equity tax-exempt funds, dating back from 1985 to 1989 that were managed by 341 different pension funds. Their measure of herding for a given stock is:

$$H(i) = \left| B(i) / B(i) + S(i) - p(t) \right| - AF(i)$$

where $B(i)$ are denoted as the net buyers, $S(i)$ as the net sellers and $p(t)$ as the 'expected proportion of money managers buying in the quarter examined, relative to the number active'. $AF(i)$ stands as the expected value of the forementioned equation under the null hypothesis of no herding. Having tested their sample, they argue that on average no much herding is being observed in individual small stocks contrary to large ones where strong evidence of herding are being resulted. However, pension fund managers may herd altogether if they receive the same information and interpret it similarly, whereas they will perform otherwise if information is uncorrelated with events. Eventually their trading does not seem to destabilize prices away from fundamentals.

To sum up, all the above suggest that there do exist issues in market efficiency due to the different perceptions of investors, due to the predictability in the pattern of stock prices and mainly due to the unusual time periods of investment performance and information sets. Investors therefore do tend to behave irrationally and drive prices away from fundamentals.

1.1.1.2. 'Anomalies' in Finance

Even if investors' sentiment is a significant issue in determining whether a market is efficient or not, seasonal patterns also play a role in justifying this matter.

According to Schwert (2003), *'anomalies in finance are empirical results that seem to be inconsistent with maintained theories of asset-pricing behaviour. They indicate either market inefficiency or inadequacies in the underlying asset-pricing model'*. Examples of some representative seasonal patterns that are related solely to returns across assets are presented below:

- *Calendar effects*

Boudreaux (1995), states that seasonal time series occur in contradiction to the weak-form of EMH in which stock returns are time-invariant i.e. there is no identifiable pattern or returns in the short-run.

The January/turn-of-the-year effect

The so-called January effect refers to the excess returns observed during the early days of January rather in any other month of the year (Rozzeff and Kinay, 1976). Their study involved a research based on the NYSE for the period of 1904 to 1974 and showed that the average stock returns are 3,5% in January compared to 0,5% in the other months of the year.

More international studies have also verified the above: in the U.K stock market (Lewis 1989); in the Canadian stock exchange (Tinic, Barone-Adesi and West 1990) and in the Tokyo Stock Exchange (Aggarwal, Rao and Hiraki 1990). However, Moosa (2007) in his research on the Dow Jones Index from 1970-1005 found that during the period of 1990 to 2005 the January effect vanished and proposed that taxation reasons have led managers to change their buy-hold decisions. The general mathematical formula can be expressed as:

$$R_t = \sum_{i=1}^{12} a_i D_{it} + \varepsilon_t \,,$$

where D_{it} takes the value of 1 if the return at time t belongs to month i (for instance January) and 0 if it belongs to any other month and a_i is the mean return in month i.

The weekend effect

The weekend effect was firstly introduced by French (1980) while he studied the mean returns of the S&P 500 composite index from 1953 to 1977 in the U.S. and found that there were significantly negative during the closing of Friday and the opening of Monday. Also Jaffe and Westerfield (1985) came up with the same conclusion. In contrast, *adverse weekend effects* were observed (Mehdian and Perry, 2001; Brusa, Liu and Schulman, 2000; Nippani and Arize, 2008) indicating that Monday returns in the U.S. stock market tend to be positive and greater than other days.

Other calendar effects include the *monthly effect* (Ariel, 1987; Gultekin and Gultekin, 1983) where stock returns are positive only for days before and during the fist half of the month and the *holiday effect* (Kim and Park, 1994) where excess returns are observed on the days prior to market closing for holidays.

➢ *Non-calendar effects*

The most well-known non-calendar effects that are related mainly to firm characteristics and other valuation parameters are the size effect, the value effect and the equity premium puzzle.

The size effect

Banz (1981) and Reinganum (1981) in their studies on the misspecification of the CAPM model they concluded that high P/E firms that were trading in NYSE index between 1936-1975 have underperformed the market whereas low P/E firms have overperformed it.

The value effect

Contrary to the size-effect phenomenon, the value effect predicted the opposite. A primary paper by Basu (1983) indicated that low P/E stock have generated higher returns for their investors. Similarly, Fama and French (1992) in their study on the U.S. stock market, from early 1960s through 1990, confirmed a strong value effect especially during the period of the Internet Bubble. Finally a recent research by Malkiel and Jun (2009) provided evidence that value-driven portfolios have overperformed the market, while using a special weighting-rank method that helped them reduce the degree of mean reversion during periods when "value" stocks underperformed the market.

The Equity Premium Puzzle

Finally an important concept to be discussed is the idea of *the equity premium puzzle*, firstly introduced by Mehra and Prescott (1985). By definition, the equity premium is the difference between the expected return on the market portfolio of common stocks and the risk-free rate. In the long-run researchers have found that stocks perform better than bonds, even if the risk is high in investing at stocks, relative in putting your money at treasury bill accounts. The answer to that paradox event came ten years later from Benartzi and Thaler (1995), who proposed two reasons in investor's behaviour that originate back at the psychology of decision-making: a.) individuals are loss-averse meaning that they are distinctly more sensitive to losses than to gains and b.) agents are 'myopic' over long horizons; the longer the timeframe perspective, the less the resistance they exhibit to taking risks.

1.1.1.3. – Stylized facts and statistical aspects in financial time-series

While the EMH has provided much evidence in explaining all the statistical properties of returns by similar characteristics when news arrive, behavioural finance models came into introducing the dynamics between heterogeneous interacting agents and their influence on stock prices and fundamentals.

Above all the aforementioned issues it would be worthwhile therefore, to include in this relevant part some stylized facts that have been developed with regards to statistical analysis in price valuation and are commonly referred when examining financial time-series.

Cont (2001) argues that the use of non-parametric methods is pretty helpful in determining qualitative assumptions and maintains the view that even if they do provide numeric information they do not seem to utilize fully the economic rationale and the usefulness of the practitioner's standpoint.

Nonetheless, stylized facts are commonly observed in financial time series and the main ones are shortly presented below:

1) *Absence of autocorrelations*: autocorrelation of asset returns are often insignificant. This is the core assumption of EMH (Fama, 1970) that has widely been tested (random walk hypothesis).
2) *Heavy/Fat tails*: the distribution of returns around the mean follows a leptokurtic pattern. Lux (1998) indicates fat tails as his main finding in his research and concludes that dynamic/chaotic processes may be a valuable explanatory of bubbles and downrushes. Alternatively if news come in with a Gaussian distribution pattern, the changes in the fundamental values of equities may be translated into a heavy-tailed distribution of price changes (Maldelbrot, 1963)
3) *Gain/loss asymmetry*: the concept of gain/loss asymmetry was firstly introduced in Physics while studying turbulence. However in economics, it has received a different meaning, incorporating time as a crucial factor. Alternative definitions are captured as "inverse statistics" and "investment horizon approach". Jensen *et al.* (2003) provide a pretty informational analysis on the concept and its implications. Their study was based on one of the major US indicators, the DIJA (Dow Jones Industrial Average) in a time period of 1000 trading days, corresponding roughly on 4 calendar years. Having considered all the econometric analysis they ended up that over short periods of time, developed market experience more losses than gains, or in other words draw downs are faster than drawn ups, at a return level of 5% in prices. In contract, emerging markets experience the inverse effect, i.e. waiting shorter time of getting gains rather than losses (Karpio et al., 2007).
4) *Aggregational Gaussianity*: As time scale Δt increases, return distribution looks more like a normal distribution, even if at different time scales the shape is not the same. Plerou et al. (1999) confirm the above as they conducted a study on U.S. stock markets; the NYSE; the American Stock Exchange and the NASDAQ and concluded that for longer periods of time (up to approximately 16 days) it is observed 'slow' Gaussian convergence of price returns.
5) *Intermittency*: According to Bickel and Lai (2001), intermittency of stationary time-series is defined as "the tendency of its absolute values, $\{|\Delta x_i|\}_{i=1}^{n-1}$, to be much greater

than the most probable absolute values" (p. 420). Thus, intermittency follows from the fact that observations differ dramatically from time to time and stock returns display a certain degree of variability. They study the concept on economic (S&P 500 index) and clinical data (adult heart rates) and found that intermittency in returns is close to zero mean and negatively skewed, however positively significant, suggesting that equity returns do not follow a random walk.

6) *Volatility clustering and conditional heavy tails*: it is widely reviewed in the literature that volatility clustering and persistent heavy tails are distinctive features of financial time-series indicating the markets are inefficient and agents are heterogeneous. Positive serial autocorrelations and fat tails are usually observed (Andersen and Bollerslev, 1997). Lux and Marchesi (1999, 2000) support that these two features are mainly attributed to the different trading strategies that fundamentalists and chartists follow in their models. In addition Kyrtsou and Terraza (2002) also comment that financial time-series exhibit the same properties. Their empirical study on CAC40 using mainly ARCH models verifies the above mentioned characteristics. They argue that in complex systems such as stock markets, we cannot easily predict their efficient nature since the heterogeneous investors' interaction drives away prices from fundamentals. Mathematically volatility clustering can be expressed as (Cont 2001):

$$C_a(\tau) = corr\left(\left|r(t+\tau,\Delta t)\right|^a, \left|r(t,\Delta t)\right|^a\right)$$

7) *Slow decay of autocorrelations over time:* An empirical study by Ding et al. (1993) on real stock data from the S&P 500 returns has proved that for various types of α, high autocorrelation effects for long lags are reported, implying a long-standing dependence that decays over time.

8) *Leverage effect:* it corresponds to negative correlations between past returns and future volatility. It was firstly discussed by Black (1975) when he supported he view that when a firm's reputation fades away, its stock returns also diminish, increasing the leverage of its stocks. Bouchaud *et al.* (2008) having used advanced econometric methods concluded that this phenomenon is persistent in U.S., European and Japanese stocks and specifically it decays over a few months in individual stocks and over much faster in stock indices.

Before proceeding to the next part of the literature review, let us consider some statistical features that affect financial time series and particularly asset returns. Real time series often seem to exhibit *non-stationary* features which in turn affect parametric analysis due to biases in their regression coefficients and lack of validity in the relevant statistical tests. For instance, consider an estimate for a non-stationary variable such as the t-stat and F-stat and suppose that it is statistically significant but of no economic value. Therefore the estimated amounts due to the inconsistency of the results may well bring up causality issues and affect the real structure of the model (mean and variance measures).

Thus, when non-linear models are considered, special reference needs to be made in order to test whether they are *stationary* and *ergodic*, or reveal certain qualities that need to be tested further. For linear models the most-commonly used measure of unit roots is the Augmented Dickey-Fuller test, firstly introduced in 1979 (Dickey and Fuller, 1979) that enables researches to find out the stochastic or not trend of the series.

In conclusion, having mentioned all the basic notions behind EMH and its weaknesses, the next part is devoted to the concept of “heterogeneity”. It will be focused on the presentation of some well-discussed heterogeneous agents’ models that are based on the stylized description of the behaviour of agents.

1.2. Heterogeneity

1.2.1. Heterogeneous beliefs and investor behaviour

The theory of efficient markets presupposes that investors behave rationally and follow Bayes rule of probability on the basis of all available information. They have homogeneous beliefs and receive simultaneously the same news that determines stock prices, in an attempt to maximize their economic utility.

However, markets are not perfect and based on empirical settings there exist internal dynamics of their own. As many studies have shown, traders interpret information in a way that makes prices diverge away from fundamentals. Markets do not process information instantaneously and agents overreact to the news due to their optimism or pessimism. As a result, trading volume and volatility of returns are higher than expected, so as calendar effects and other phenomena are observed. Investors realize markets as 'fertile grounds' for speculation and do engage in situations where they behave irrationally giving the impression that markets are dominated by actions of people. Therefore incidents such as herding or even bubbles and crashes occur. Consequently, markets are characterized by a presence of heterogeneity in traders and especially in their conception about risk, return, prior beliefs and information

All the forementioned features are undoubtedly true when considering the EMH and formed an advanced approach of finance – *the behavioural finance.* The stylized facts analysed in the previous section, as well as the different investor categories/strategies (fundamentalists, noise traders, feedback traders) and the imperfections of the financial systems (predictability of prices) have managed to extend this alternative view in recent theory.

Daniel *et al.,* (2002) provide a review on the cognitive errors that investors engage in while trading and argue that various psychological resources such as time, memory and attention help them form their optimal decision making process. On the investor's point of view they claim that private or even institutional investors often do not participate freely in the 'buy-and-sell' process of different assets and securities with the excuse that they are not familiar with the method.

Additionally, Tversky and Kahneman (1991) using the indifference curves in their study, found out that agents might have similar beliefs or reference points about their choices, however it is not the fact that their expectations about gains or losses are identical.

They exhibit a loss-averse behaviour indicating that they are willing to maximize their expected utility by realizing more gains mainly by pursuing appropriate strategies of 'keeping winners and selling losers'.

Furthermore, Daniel *et al.* (2002) also make reference on the way investors trade and mention that agents sometimes become aggressive in the process, in order to earn excess returns and eliminate information asymmetry (DeBondt and Thaler, 1995; Wang, 1998) thus large trading volumes are being observed as a result of their overconfidence. Additionally, this irrational behaviour of individuals leads to blatant errors that are attributed to the misperceptions they have about their models.

However, an important question in heterogeneous agents' behaviour is whether irrational traders can survive in the market or they will be eliminated by the rational ones. Many papers have contributed to this research and most significantly the one where DeLong et al., (1990) have proved that in the long-run noise traders will outperform the market and may survive with positive returns[4]. Similarly in a related work Brock *et al.* (1992) concluded that technical strategies applied to a set of data in the Dow Jones index also outperformed the market.

Finally a number of papers have given emphasis on the heterogeneity of beliefs that leads to market instability, complex dynamics and chaotic fluctuations. For instance Chiarella (1992) in his paper denotes that in a nonlinear model where fundamentalists and chartists trade, asset price fluctuations are caused by an endogenous mechanism where a large fraction of the fundamentalists tends to stabilize prices, whereas a large fraction of chartists tends to destabilize them.

To sum up, it is evident that the large number of participants in the markets (individual investors, mutual/hedge funds, private investors, traders) as well as the speed of information, its misinterpretation and the different trading strategies, can all justify the heterogeneous nature of the financial markets that dominates today's economic environment.

In the next part, there will be a brief presentation of the most important heterogeneous agent models that validate the existence of heterogeneity in markets and their implications in behavioural finance as a whole. Specifically, in each model it is going to be discussed the econometric method, the type of agents and the main findings of the survey along with the financial developments applied within.

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[4] This paper will be presented in the next section of part 1.2.

1.2.2. Heterogeneous agent models

In the recent literature quite a number of heterogeneous agent models (henceforth HAMs) have been developed, providing an extensive view of the heterogeneity of investors and their dynamic nature in economics and finance. Some of them will be presented below:

❖ *The Cutler, Poterba and Summers (1990) model*

Cutler *et al.* (1990) attempted to define an alternative way of explaining speculative dynamics while their survey is based on real monthly data on various investment options such as U.S. equities, bonds, exchange rates and gold. They concluded that in the short run (1-12 months) excess returns with positive autocorrelation are being realized. In the mid-run (13-24 months) there is a weak tendency for less autocorrelation (not statistically significant) while in the long-run (periods of several years) and in order to predict correctly returns on prices, proxy variables should be used.

Therefore, with the aim of studying the above relationship Cutler *et al.* (1990) propose three groups of traders. The first group is denoted as *the rational traders* since they invest on the basis of rational forecasts of future events. Their demand for assets is:

$$s_{1,t} = \gamma\left(E_t R_{t+1} - \rho\right), \qquad \gamma > 0$$

where R_t is the ex post return in period t and ρ is the required rate of return for the risky asset. As the gap between $\left(E_t R_{t+1} - \rho\right)$ is deviating further from the price of the risk free asset, the demand will increase as well.

The second group of investors is *the fundamentalists*. They base their expected returns on prices according to the fundamental price and when the returns are higher to fundamentals, their demand for an asset seems to be low:

$$s_{2,t} = \beta(p_t - a(L) f_t), \qquad \beta < 0, \quad \alpha(1)=1$$

where, p_t is the logarithm of prices, f_t the logarithm of true fundamentals and $a(L) f$ the perceived fundamentals. As previously stated, as the gap between $(p_t - a(L) f_t)$ increases, the fundamentalists' demand for as asset will decrease, given β < 0.

The third group of traders is *the feedback traders* who base their demand on:

$$s_{3,t} = \delta(L)(R_t - \rho)$$

where $\delta(L)$ is a random lag polynomial. Cutler *et al.* (1990) mention that for positive feedback trading, i.e. buy when prices are increasing and sell when they are falling, one can use various techniques such as stop-loss orders, portfolio insurance, positive wealth elasticity of demand for risky assets and margin call-induced selling. In contrast, considering the negative feedback trading, i.e. buy when prices are falling and sell when prices are increasing, the most appropriate strategy in order to experience excess returns is the 'profit-taking' strategy as markets are rising.

Having specified the demand functions, they argue that for market equilibrium it is required:

$$s_{1,t} + s_{2,t} + s_{3,t} = 0$$

They propose that these three groups of investors are interacting together and they separate their effects under the hypothesis that their relation generates positive and negative serial correlation. First, considering a situation where no feedback traders are present and information if fully absorbed in the prices. The outcome of the workout between fundamentalists and rational traders would be a positive autocorrelation in prices, since capital gains will be enough to offset the long position of fundamentalists. An other source of positive autocorrelation would be the scenario of no fundamentalists in the market and only negative feedback traders are involved ($\delta(L) < 0$). Then 'good news' induce negative feedback traders to decrease their demand for an asset, whereas rational investors would leave their long positions by increasing their expected returns and profits.

Finally, positive feedback traders can create positive autocorrelation in the short-run and negative in the long-run, driving prices away from fundamentals.

To sum up, the main purpose of the article is to provide enough evidence on the speculative dynamic forces that exist between heterogeneous agents and how they can lead to instability in prices and fundamentals. Their numerical results show that for short horizons positive feedback trading brings prices closer to fundamentals but also increases feedback demand for the next periods and as a result the variance in prices changes and profitable speculation is being realized.

❖ *The DeLong et al. model (1990a, 1990b)*

Prior to arguing about the model and its implications it would be worthwhile to stress out the idea of a new trader type that got into the literature – *the noise traders*. Black (1986) firstly introduced the concept and defined it as 'what makes our observations imperfect'. He used the word in several senses from the finance and econometrics point of view, to the macroeconomic theory. He claimed that noise makes financial markets inefficient and makes trading possible in the sense that people would trade also on noise and not only on rational information, even if this would put an additional 'ingredient' in the price. However, all the above are nowadays prone to judgment and criticism, since this particular paper was lacking of empirical foundations.

Moving forward, DeLong *et al*. (1990a) (henceforth DSSW) begin their analysis by referring initially to the risk that noise traders bring to the market. They distinguish two groups of traders; the noise traders and the arbitrageurs. They mention that short-term horizon investors (arbitrageurs) create more risk in the market than noise traders. If noise traders become pessimistic about an asset and have already driven downwards its price, an arbitrageur buying this asset must bear in mind that in the near future its price might be even lower if noise traders continue being pessimistic. If arbitrageurs wish to liquidate before the asset recovers, they accept a significant loss. In contrast, DSSW showed that noise traders, who are on average bullish, earn higher returns than sophisticated traders, due to the fact that noise trading makes assets less attractive to risk-averse agents (arbitrageurs) and imposes further pressure on prices to fall. As they say 'arbitrage does not eliminate the effects of noise because noise itself creates risk', therefore noise traders experience larger returns on the risk they themselves create in the market.

Moreover, among the various considerations posed in the article, DSSW propose a model of rational and noise traders where risk is fundamental in the process. Their basic model is a stripped-down overlapping generations one with two-period-lived agents. Two types of agents are assumed, the noise traders (n) and the rational traders (i). Two are the assets as well; a safe asset (s) paying a dividend r and a risky asset (u) paying an uncertain dividend:

$$r + e_t, \quad \text{where } e_t \sim N(0, \sigma_e{}^2)$$

The demand functions for the rational traders and for the noise traders are the following ones:

$$\lambda_{\tau}^{\iota} = \frac{r + E_t p_{t+1} - (1+r) p_t}{2\gamma(\sigma_{p_{t+1}}^2 + \sigma_e^2)}$$

$$\lambda_t^n = \frac{r + E_t p_{t+1} - (1+r) p_t}{2\gamma(\sigma_{p_{t+1}}^2 + \sigma_e^2)} + \frac{\rho_t}{2\gamma(\sigma_{p_{t+1}}^2 + \sigma_e^2)}$$

where γ is the coefficient of risk-aversion, $E_t p_{t+1}$ is the expected price at time t+1 and $\sigma_{p_{t+1}}^2$ is the expected one-period variance of p_{t+1}. ρ_t is the misperception that noise traders have about the tomorrow's expected price for an asset by the noise trader.

It is being asserted that noise traders take advantage from the information they receive about the future price of a risky asset (sentiment), selecting portfolios that are solely constituted upon their beliefs. In contrast, rational traders use the signals from the noisy ones and buy when noise traders push prices up. This strategy enables prices reach their fundamental value but not completely. The equilibrium price equation if fundamental risk is included becomes:

$$p_t = 1 + \frac{\mu_t \rho^*}{r} - \frac{2\gamma}{r}\left[\sigma_e^2 + \frac{\mu^2 \sigma_\rho^2}{(1+r)^2}\right] + \frac{\mu_t(\rho_t - \rho^*)}{1+r}$$

However, the important issue here is which type of agents earns the highest possible returns. DSSW compute the expected difference of return between the two types of traders:

$$E\left[\Delta R_{n-i}(\mu)\right] = \rho^* - \frac{\rho^{*2} + \sigma_\rho^2}{2\gamma\left[\frac{\sigma_\rho^2 \mu}{(1+r)^2} + \frac{\sigma_\varepsilon^2}{\mu}\right]}$$

and it follows that for the noise traders to earn more ρ^* must be positive and γ should be large enough. Since noise traders who are said to be bullish take on more risk than the rational investors, as long as the market rewards that risk (either fundamental or not) then noise traders can earn higher returns even if they buy high and sell low.

Overall, apart from the effects described above and are related to the adjustment in the market risk, there is also an other matter to be addressed – the one that has to do with the survival of noise traders. Fama (1965) in an early paper advocated that irrational traders (noise traders) due to the fact that they trade against the rational ones and mistakenly drive prices away from fundamentals; they will be eliminated by the market.

DeLong et al. (1991) conducted a further study and added in their analysis the long-run distribution of wealth so as to examine a model in which noise traders do not affect prices. They used a one-period and a multi- period model based on the assumptions of 'survival' and 'dominance' as stated below:

$prob\left(\omega_t^x \rangle \varepsilon_1\right)\rangle \varepsilon_2$ for a given group of investors *x* that 'survive in the long-run' if their share of the economy's total wealth (ω_t^x) does not approach zero as time goes by.

$prob\left(\omega_t^x \rangle \omega_t^y\right)\rangle \frac{1}{2}$ for a given group of investors *x* that 'dominates' group *y* if *x*'s share of the economy's total wealth (ω_t^x) is greater than one half of the share of *y*'s.

They end up claiming that noise traders do survive in the long-run with a relative wealth that does not drop below zero and they do not affect prices. In contrast, Hirshleifer and Luo (2001) provide an alternative view of the survival of noise traders. They support that overconfidence is ‘an overestimation of the precision of private information signals’ while prices are derived endogenously as irrational traders push them towards their side (e.g. by buying certain equities such as internet stocks). In addition, high profits in their model arise from the overreaction in prices as noise traders are trading aggressively in the market, whereas DeLong *et al.* (1991) argue that overconfidence is mainly driven by the underestimation of risk that their portfolios bear.

In addition to the analysis of the HAMs, DeLong *et al.* (1990b) considered a different model where noise traders are replaced by *positive feedback traders*. By definition positive feedback is regarded as a strategy where investors ‘buy stock when prices are rising and sell them when they are falling’. In this paper DSSW wanted to defend Friedman’s hypothesis (1953) and prove that under positive feedback trading rational speculation can be destabilizing.

The main findings of their study show that in the presence of feedback trading strategies, rational speculation can be destabilizing. The overreaction to news caused by rational informed speculators due to the noise traders’ activity can make positive feedback traders even more excited and so move prices further away from their fundamental values, than they would be in the absence of rational speculators.

❖ *The Sentana & Wadhwani model (1992)*

So far, the above mentioned models tested the effects that noise and feedback traders exerted on expected returns. The aim of Sentana and Wadhwani was to look further and examine the links between volatility and serial correlation. They introduced the concept of ‘non-synchronous’ trading as a possibility of increased correlation as well as they gave emphasis to the investors’ wealth in explaining their results.

Their study was conducted by using both hourly data around the period of the October 1987 crash and daily data for 1885-1988 derived from the Dow Jones, from the S&P composite and from the CRSP value-weighted indices. Alternative measures of volatility were implemented based on a standard GARCH specification, an exponential GARCH model and also on non-parametric methods.

The main model presupposes two types of agents; smart money and positive feedback traders. Their demand functions are the following:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\mu_t} \text{ for smart money} \qquad (1)$$

$$Y_t = \gamma r_{t-1} \text{ for positive feedback traders (i.e. } \gamma > 0) \qquad (2)$$

Following (1), r_t is the ex post return in period t, E_{t-1} is the expectation operator at time t-1, α denotes the return at which the demand for shares by this group is equal to zero and μ_t is the risk premium for holding further all the shares. Assuming that $\mu_t = \mu(\sigma_t^2)$ with $\mu>0$ these particular investors are said to be risk-averse. So if volatility increases, the relevant risk premium for keeping the shares of the smart money agents increases as well. Additionally, γ in eq. (2) depends on current wealth. Market equilibrium requires that:

$$Q_t + Y_t = 1 \qquad (3)$$

which gives from (1) and (2):

$$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2) r_{t-1} \qquad (4)$$

When testing for non-synchronous trading, they conclude that if a high trading period with extreme volatility in prices is considered, then non-synchronous trading would be evident and would be a reason to the serial correlation of returns.

Moreover, they separated their empirical evidence into two categories – evidence based on hourly data around the October 1987 crash for the U.S. and the U.K. and daily data from 1885 to 1988. In the first instance, they estimated the following:

$$r_t = \alpha + (\gamma_0 + \gamma_c Crash_t) r_{t-1} + \varepsilon_t \qquad (5)$$

where $Crash_t$ is 1 during the crash week and 0 otherwise, using hourly data for both the countries.

Analysis proved that in the U.S., as the crash was more intense than in the U.K., negative serial correlation was observed since high volatility induced smart money agents to be more cautious, allowing at the same time portfolio insurers and stop-loss traders to exert more power on prices. In contrast, in the U.K. returns exhibited positive serial correlation due to non-synchronous trading and/or negative feedback strategies. However, during the crash week the coefficient turned out to be negative. With regards to the daily data subset, they found that higher volatility is more likely to yield negative serial correlation.

To sum up, their empirical work reported that at low volatility levels, short-run returns show positive serial correlation and negative when looking at the long-run. This evidence is consistent with the non-synchronous trading effect. As volatility increases, positive feedback traders influence prices more, pushing along greater negative serial correlation in returns. Consequently, taking the possibility of risk-aversion into account and the effect of distress selling after prices declines, they supported that positive feedback trading is greater after price drops that it is after price increases.

Chau *et al.*, (2011) attempted to extend the S&W model by allowing the demand of feedback traders to be sentiment-driven. They used a data set of U.S. ETFs from 2000 to 2007 under the following condition in feedback traders' demand function:

$$F_t = \gamma R_{t-1} + \lambda D_t$$

where D_t is a dummy variable that is equal to 1 in a period of high investor sentiment (optimistic) and 0 in a period of low investor sentiment (pessimistic). They propose a negative autocorrelation and volatility of ETF returns when positive feedback traders are interacting in the market, whereas the level of feedback trading is also influenced by sentiment. Specifically optimistic investors are more likely to chase the trend even if the market might be bullish.

Similarly, Koutmos and Saidi (2001) in their study on emerging capital markets (Hong Kong, Malaysia, Philippines, Singapore, Taiwan and Thailand) found that positive feedback trading strategies can induce significant autocorrelation. They have also found high volatility, even if trading seems asymmetric in up and down indices with regards to developed stock markets. They attribute this evidence to portfolio insurance and stop-loss orders.

❖ *The Chen et al., model (2001)*

The models mentioned above are based on real data and to an ongoing situation where the different types of agents are presumably trading in a natural financial environment. The Chen et al. (2001) model extends the analysis and provides a new insight on HAMs by testing heterogeneity in an artificial market. Their main interest was in interpreting the behaviour of two different types of agents while testing for chaos conditions in simulated data. It is being referred that their present study is in line with the research of Lux and

Marchesi (1999, 2000) when they tested the presence of unit roots and asset price dynamics along with heteroscedasticity and leptokurtosis of returns.

They distinguish three groups of traders. First, the fixed number of traders in the market (N) that is being separated into two subgroups; the noise traders and the fundamentalists with $n_n(t)$ and $n_f(t)$ the number of agents in both groups (note that $N = n_n + n_f$). Secondly the group of noise traders consists of those who are optimistic and those who are pessimistic and their numbers are given by $n_+(t)$ and $n_-(t)$, where $n_+(t) + n_-(t) = n_N$. Their strategy is solely dependent upon the decision-making process of the remaining agents and on the trend of actual prices, i.e. $(dp/dt)/p$.

Furthermore, the probabilities of switches between optimistic and pessimistic groups are the following ones:

$$\pi_{+-} = u_1 \frac{n_n}{N} \exp(U_1)$$

$$\pi_{-+} = u_1 \frac{n_n}{N} \exp(-U_1), \quad U_1 = a_1 x + \frac{a_2}{u_1} \frac{dp/dt}{p}$$

Here the parameters u_1, a_1 and a_2 relate to the frequency that traders pursue in revaluating opinions and the importance of majority opinion and trend respectively.

On the other hand, the probabilities of switches from the noise trader to fundamentalist groups are formalized as:

$$\pi_{+f} = u_2 \frac{n_+}{N} \exp(U_{2,1}), \quad \pi_{f+} = u_2 \frac{n_f}{N} \exp(-U_{2,1})$$

$$\pi_{-f} = u_2 \frac{n_-}{N} \exp(U_{2,2}), \quad \pi_{f-} = u_2 \frac{n_f}{N} \exp(-U_{2,2})$$

The terms, $U_{2,1}$ and $U_{2,2}$ are denoted as the ones below, as they calculate the profits earned by noise traders and fundamentalists:

$$U_{2,1} = \alpha_3 \left[\frac{r + \frac{1dp}{u_2 dt}}{p} - R - s \left| \frac{p_f - p}{p} \right| \right],$$

with $\frac{r + \frac{1dp}{u_2 dt}}{p} - R$ the noise traders; profit from group n_+

and $s\left|\frac{p_f - p}{p}\right|$ the fundamentalists' profit.

$$U_{2,2} = \alpha_3\left[R - \frac{r + \frac{1dp}{u_2 dt}}{p} - s\left|\frac{p_f - p}{p}\right|\right],$$

with $R - \frac{r + \frac{1dp}{u_2 dt}}{p}$ the noise traders' profit from group n_-

and $-s\left|\frac{p_f - p}{p}\right|$ the fundamentalists profit.

R is the average real risk-adjusted return, *r* are denoted as the nominal dividends, *p* the price of the asset, p_f the fundamental value and *s* as a random discounting factor.

The interaction between the groups is realized pursuing the corresponding actions and adding in the 'game' effect of a market maker who reacts on imbalances between demand and supply; when the optimistic noise traders are on the demand side of the market, then the observed excess demand is attributed to the number of individuals and to the main two groups of traders so as if t_n is the mean volume of transactions the,

$$ED_n = (n_+ - n_-)t_n$$

and the excess demand of fundamentalists is:

$$ED_f = \frac{n_f \gamma (p_f - p)}{p},$$

γ being a parameter for the strength of reactions between *p* and p_f.

Chen et *al.* (2001), introduce and exogeneous shock in news and create an internal value logarithm according to Wiener process as:

$$\ln(p_{f,t}) = \ln(p_{f,t-\Delta t}) + \varepsilon_t \Delta_t,\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

With this way they validate that stylized facts as volatility clustering, fat tails and non-linearity are not influenced by information. Therefore their justification is based only on the interaction of the market dynamics.

In addition they perform three statistical tests in order to examine the existence of non-linear patterns. Those are the *fractal dimension* test, the *BDS* and *Kaplan* test and the *GARCH estimation* test. Overall and under the empirical results of the forementioned tests it is presented that there is no convergence of events. It appears that 'the price dynamics from their model are less complex than the pseudo-random number underlying the dynamics of the fundamental value' (pp. 333).

Literature on HAMs has provided many more models or even alternative approaches of the ones mentioned before. Thurner *et al.*, (2002), present a dynamic asset pricing model of heterogeneous investors who act on different time scales. They find fat-tailed distributions and non-significant autocorrelations of returns but significant positive ones for squared returns. It allows for the creation of speculative bubbles that can either be triggered by news about fundamentals or by abnormal technical trading.

Similarly, Sansone and Garofalo (2007) have built their study on the previous model and present a continuous time-dynamic model in which three different types of agents take part; the fundamentalists, the trend followers and the contrarians. They also derive the same stylized results as Turner *et al.*,(1989); i.e. excess kurtosis, volatility clustering and long memory however they also denote that even when only fundamentalists are trading in the market, they seem to be unable to move prices away from fundamentals. As a result, they introduce disorder in the system by causing trend followers and contrarians to give rise to synchronization in the system by leading to dramatic changes within it.

Westerhoff (2004) presents a behavioural model in which traders are mainly influenced by greed and fear. They estimate that stock prices increase over time while periods of low and high volatility are apparent, resulting in low autocorrelation effects and crashes. The empirical analysis concluded that the emotional regimes referred above may play a role in determining prices but further study needs to be done.

Finally a very interesting research has been carried out by Huang *et al.* (2010) on the ability of heterogeneous agents to create financial crises. The model is constructed around two types of investors; the fundamentalists and the chartists. They formulated their demands for assets according to fundamental values. Three distinct categories of crises are being tested; namely the sudden crisis, the smooth crisis and the disturbing crisis.

According to the researchers, a sudden crisis occurs when a price for an asset sinks abruptly from the peak down to the bottom in a very short time frame, whereas a smooth crisis occurs when there is a succession of downward price waves in a no visible way. Disturbing crisis may be visible but not as dramatic as a sudden crisis even if it lasts longer.

Both fundamentalists and chartists can create all the types of crises along with the endogeneous price dynamics that overpower the markets albeit exogeneous shocks may well ‘lit the fire’.

Was the financial crisis of 2007-… attributed to emotional/psychological factors or the lack of proper fiscal and monetary policy has caused it?

As all the above suggest that market efficiency is no longer an issue, HAMs offer an alternative explanation about nowadays turmoils in financial markets. Many strategies have been addressed while our main study will be focused on the feedback ones that are going to be analyzed in the next part of the review.

1.3. Feedback Strategies

So far we have presented the basic theory and HAMs that lie behind the behavioural finance models. In this part we will extend the analysis and provide further evidence with regards to the so-called *feedback strategies*. Researchers have identified, among others, three different agent types, namely the *fundamentalists*, the *rational traders* and the *positive feedback traders*, that affect price dynamics and lead prices away from their equilibrium levels.

For the later, we distinguish two main strategies; the positive feedback strategies and the negative ones. In most of the literature, negative feedback trading is not being observed as it refers to 'buying past losers and selling past winners', something that out of common sense is not pretty straightforward. Therefore, we will focus on the positive feedback trading and its main findings.

Positive feedback trading can result either from predictive expectations about prices or even from trend chasing attitudes. It can also result from stop-loss orders, from portfolio insurance and from margin calls, as cited earlier.

To begin with, Arthur (1989) presents an alternative concept of positive feedbacks that rule the economy as a whole and claimed that the positive feedback theory or else the *increasing-returns theory* had strong connections with the modern non-linear physics, new technology economies or even evolutionary thinking too. He provides many examples of positive feedbacks and supports the view that there are several instances where positive feedback loops can occur and broaden the possibilities of engaging into a system that continuously evolves over time.

Strictly speaking about financial markets, positive feedback trading results into excess volatility and long-run reversals that are simultaneously affected by herding. Nofsinger and Sias (1999) in their study concluded that institutional ownership provokes positive correlation contrary to individual one, since institutional herding is more powerful and impacts prices more. Similarly, as institutional investors attract more low transaction costs equities, as their price increases the relevant costs will diminish inducing further excess returns to the stockholders. Likewise, Choe *et al.,* (1999) while studying the Korean crisis in 1997, commented that herding effect can destabilize markets since foreign investors trade as a group ('flock of sheeps') thereby creating panic when they drop out of the market or even trigger the market when they enter it. Strong evidence of positive feedback trading and herding are being observed before the crisis whereas during the crisis and after it the evidence tend to be weaker.

Moreover, Farmer and Joshi (2002) examine different trading strategies and their effects on price dynamics by proposing a *price impact function* that relates the market orders made by the various agent types with the relative changes in demand. They assume three broad agent types; *the value investors* (or fundamentalists), *the trend followers* (or chartists) and *the market makers*. Then they subcategorize these agents into the *directional* ones who buy and sell orders and the *market maker*. Initially, the order is determined as:

$$\omega_t^{(i)} = x_t^{(i)} - x_{t-1}^{(i)}$$

and the dynamic interaction between trading decision is prices is:

$$p_{t+1} = p_t + \frac{1}{\lambda}\sum_{i=1}^{\mathrm{N}} \omega^{(i)}(p_t, p_{t-1,\ldots,}\mathrm{I}_t) + \xi_{t+1}$$

where ξ_{t+1} is the noise that relates to the orders that are submitted randomly and λ is a scale factor that normalizes the size of the order and is called liquidity.

They suggest that according to the information set, there are two decision rules that drive agents' behaviour; the trend strategies and the value strategies. Trend followers place their positions according to the recent price changes while value investors are affected by external information leading to a subjective assessment of the long-term equilibrium value of the prices. They conclude by mentioning that short-term positive autocorrelations are being detected following the trend strategies, contrary to negative long-run autocorrelations of value strategies. In the first instance, noise in information is being amplified along the frequency of the data and thus excess and clustered volatility is being observed whereas in the second case information is being incorporated directly into prices.

Ramirez *et al.* (2003), using the same model developed by Farmer and Joshi (2002), found out that the strategies being deployed by trend followers lead to fat tails and long-run memory, as well as adaptation mechanisms and learning are necessary in order agents use them so as to bring about effective stabilization into the market dynamics.

Hirshleifer *et al.* (2006) provide an alternative point of view on feedback as a concept by discussing the view of irrational trading on market prices and profitability. They suggest that irrational trading does not provide profit opportunities to uninformed investors, even if they know that more players are trading in the markets. The risk measure is being tested as under previous literature irrational traders can earn high average returns by being exposed to systematic risk. In their model, prices are set by a form of risk-neutral market makers so that expected returns are not attributed to the excess risk, in the absence of private information.

They continue by arguing that feedback and sentiment play a significant role in determining the profits gained from the relevant strategies that various agents follow as in per se a bullish market. Those affected early by sentiment can easily earn money and while the feedback effect influences the fundamental value of prices, irrational investors can experience high positive expected returns. Thus they earn high profits that can potentially exceed those gained by rational investors, as information still continues to be private.

Furthermore, Bange (2000) in an early paper examines how sentiment and positive feedback trading cause the average equity holdings of small investors to vary over time. She claims that market timing is crucial in determining the proper strategy and via the use of simple regression models she receives significant results. She suggests that investor sentiment changes, relative to which market they are trading to (bull or bear market) may trigger changes in equity holdings as well, by adjusting to the proper equilibrium levels. Additionally, proper market timing proclaims predictability in prices and thus positive feedback trading when there are limit-ups or even limit-downs in markets. Small investors' portfolios therefore do reflect positive feedback trading, given their willingness to bear risk as their accumulated wealth rises.

Alternatively, Balduzzi *et al*., (1995) combine the positive and negative feedback strategies in a model of two investors' types (speculators and feedback traders), where stocks and bonds are traded frequently and examine their effects on asset price dynamics. Investors tend to rebalance their portfolios according to price fluctuations and 'manipulate' information as they are firstly introduced into the market. They end up saying that positive feedback trading provokes excess volatility, whereas negative feedback trading makes prices volatile less and dividends less responsive to changes in news. Seemingly, either value investors or speculators tend to adhere to the proper strategy as the relative wealth improves over time.

Moving forward and in contrast to the common view that positive feedback strategies result in positive autocorrelation of returns, Koutmos (1997) finds negative autocorrelation in stock returns. He uses the Sentana and Wadhwani model (as described above) where he distinguishes two heterogeneous groups of investors; the smart money and the positive feedback traders. The corresponding demand functions are:

$$Q_{1,t} = \frac{\left[E_{t-1}(R_t) - \alpha\right]}{\theta\sigma_t^2} \text{ for smart money investors, } \theta > 0 \qquad (1)$$

$$Q_{2,t} = \rho R_{t-1} \text{ for positive feedback traders, } \rho > 0 \tag{2}$$

Equilibrium is reached in the market when $Q_{1,t} + Q_{2,t} = 1$. From (1) and (2) we get the following:

$$E_{t-1}(R_t) = \alpha + \theta\sigma_t^2 - \theta\rho\sigma_t^2 R_{t-1} \tag{3}$$

The term [$-\theta\rho\sigma_t^2 R_{t-1}$] assumes that positive feedback trading will bring about negative autocorrelation of returns, as volatility becomes higher. Converting (3) into a regression equation with a stochastic error term by setting $R_t = E_{t-1}(R_t) + \varepsilon_t$ we get:

$$R_t = \alpha + \theta\sigma_t^2 - \theta\rho\sigma_t^2 R_{t-1} + \varepsilon_t \tag{4}$$

As non-synchronous trading is apparent the form in equation (4) cannot be tested and in contrast Koutmos used an empirical version of it:

$$R_t = \alpha + \theta\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varphi_2 \left|R_{t-1}\right| + \varepsilon_t \tag{5}$$

Positive feedback trading is denoted with the term [φ_1] and is assumed to be negative and statistically significant, while the term $\varphi_2 \left|R_{t-1}\right|$ implies the asymmetry in the model. However, if $\varphi_2 > 0$ then negative returns will be followed by more feedback trading.

The data used are derived from six industrialized countries such as Australia, Belgium, Germany, Italy, Japan and the U.K. Running the above mentioned regression model and getting the appropriate maximum likelihood estimates of the feedback, it is being concluded that the sign of φ_1 is always negative and statistically significant, implying that positive feedback trading invokes short-term movements in all six markets. Due to that, it is argued that arbitrage opportunities are unlike to happen for rational investors as volatility rises.

In addition, in four out of six markets, it is being observed that when market declines, positive feedback trading is stronger, an event that can be attributed to portfolio insurance strategies and to the use of extensive stop-loss orders.

On top of that, Antoniou *et al.* (2005) and Salm and Schuppli (2010) provide a different point of view with regards to positive feedback trading and extend their analysis on its impact on futures prices in spot markets. The basic empirical testing procedure is performed using the model that is mentioned before (Sentana & Wadhwani, 1992) leading to adverse results. In the first study, positive feedback trading strategies are not realized when futures are introduced in the spot markets, therefore prices are stabilized promptly. However, in the pre-futures period, positive feedback trading has significant impact in stock returns, pushing prices away from fundamentals. In contrast, in the post-futures period the phenomenon is weakly presented, arguing that traders are interchanged between spot and future markets.

In the second study, it is being addressed that trend-chasing behaviour is being detected strongly under periods of aggressive financial turmoil associated with falling prices. This can be explained as investors who hold long positions in futures, as prices are falling, they will find themselves liquating their spots (positive feedback effect) and driving prices further downwards. On the other hand, rational investors who wish to hedge risk will realize that too much ‘noise’ is being introduced into the market, thus limiting the effects of arbitrage and worsening their possibilities for relative profits. Similarly with the previous research, Antoniou and Koutmos (2008) also find evidence supporting the view that there are negative time-varying autocorrelations in future markets.

Moreover, further studies have been conducted with respect to feedback trading in the view of dealing with the foreign exchange market. A representative study was prepared by Laopodis (2005), who examined the impact of feedback trading, asymmetric information and autocorrelation in returns in several industrial and emerging economies’ exchange rates, compared to the US dollar. His method is pretty straightforward and was based on the initial model developed by Sentana and Wadhwani (1992), with two groups of traders; the noisy ones and the smart money agents. Daily observations for the closing spot prices of eleven non-EU exchange rates were collected from January 1st 1990 to December 30th 2003. The empirical findings using a GARCH-augmented model proved that both positive feedback and asymmetric behaviour are apparent to emerging and developed economies.

Finally, two very important papers are being presented. The first one deals with the positive feedback strategies in multivariate time series by examining the causal relationship between metal prices and US inflation, developed by Kyrtsou and Labys (2007). It is being argued that due to the complex behaviour of heterogeneous agents, prices tend to deviate from fundamentals and thus leading to sudden shocks that create instability in markets. Following that their main methodology is based on the noisy Mackey-Glass model as below:

$$X_t = \alpha_{11}\frac{X_{t-\tau_1}}{1+X_{t-\tau_1}^{c_1}} - \delta_{11}X_{t-1} + \alpha_{12}\frac{Y_{t-\tau_2}}{1+Y_{t-\tau_2}^{c_2}} - \delta_{12}Y_{t-1} + \varepsilon_t\,,\ \varepsilon_t \sim \mathrm{N}(0,1)$$

$$Y_t = \alpha_{21}\frac{X_{t-\tau_1}}{1+X_{t-\tau_1}^{c_1}} - \delta_{21}X_{t-1} + \alpha_{22}\frac{Y_{t-\tau_2}}{1+Y_{t-\tau_2}^{c_2}} - \delta_{22}Y_{t-1} + u_t\,,\ u_t \sim \mathrm{N}(0,1)$$

where α and δ are the estimated parameters, τ is the delay and c a constant. They choose the best delays according to a likelihood ratio test, bearing in mind that they do tend to change dramatically throughout time.

Initially they look at the nature of causality and furthermore to the direction of the nonlinear feedback, if it exists. If the causality between metal prices and inflation is unidirectional then (α_{12}-δ_{12}) or (α_{21}-δ_{21}) must be statistically significant or else for bidirectional causality both the forementioned differences should result to statistically significant results. Alternatively, they end up checking the feedback effects; either positive or negative, dependent on the sign of differences referred above (larger or smaller than zero). Their results reveal positive non-linear feedback relationship between commodity prices and US inflation, as metal price increases induce inflation to absorb the corresponding change in consumer prices. However, as it is being pointed out in an earlier study (Kyrtsou and Labys, 2006), in order to justify better the dynamic and non-linear nature of the commodity price fluctuations mentioned above, policymakers need to consider carefully the interactions of various macroeconomic and financial variables together and not alone.

In conclusion, an equally important aspect of positive feedback trading was presented by Kyrtsou and Terraza (2002). They maintain the view that stock markets are fully governed by non-linear dynamics that provoke complex procedures via feedback strategies and increasing returns. The heterogeneity of agents and the noise they bring into the market, leads to some sort of chaos in all financial systems, inducing price fluctuations and destabilization.

Moreover, their study is based on the Chen *et al.* (2001) model, as described in the previous part, so as to show that the different trader's characteristics can drive to 'stochastic chaotic evolution of the price series'. Applying advanced econometric models on the Paris Stock Exchange daily returns (CAC 40) from 07/09/1987 – 28/05/1999, as well as several different tests (fractional integration test, correlation dimension method, Lyapunov exponents method and forecasting techniques) they find that short memory effects in addition to noisy chaotic processes are apparent. The corresponding market is managed by complex procedures and exhibits less possibilities for applying the proper forecasting practices in order to correct for discrepancies over the long run.

On top of that, the positive feedback mechanism theoretically, is developed as: Suppose asset prices increase. At that moment feedback traders enter the market and more sellers expect prices to increase more, thus creating noise. This has an immediate effect on equity stocks by accumulating more of them. The loop continues until easy money is being realized creating an obvious trend. As a result rapid moves to instability bring about booms/crashes by introducing excess volatility in the system. Following that, the market cannot keep up its pace and prices start falling, sellers are becoming more anxious about their investments and future profits and buyers are now expecting prices to fall even further, hence agents are trying to close their short positions adding further attributes to the positive feedback spiral that goes around.

Summing up, so far it has been presented the efficient market hypothesis and its limitations that prove the weaknesses of the concept and the evolution of heterogeneous markets. Following that, heterogeneous beliefs and different agent types have been presented with emphasis to the stylized facts that describe better the abnormalities in the system. Excess volatility, complex structures and non-linear dynamics are those that characterize markets as a whole and bring about positive feedback patterns that govern today's financial marketplaces.

The next part of the thesis is devoted to an empirical analysis related to the identification of the impact of heterogeneity into risk premium evolution in Dow Jones and S&P 500 indices.

Chapter 2 – Empirical Analysis

2.1. Introduction

The second chapter of the study will entail all the empirical analysis on the various investment strategies deployed between the Dow Jones index and S&P500 index in the U.S. between 1957 and 2011, under the assumption of a newly develop model called (G)ARCH-M-MG.

The methods used in order to test the corresponding financial time series are:

- The Augmented Dickey Fuller (ADF) test
- The ARCH/GARCH model
- The ARCH-M model
- The univariate noisy Mackey-Glass (MG) model

2.2. Data

The research is conducted using daily data from the Dow Jones index and the S&P 500 index, as well as the U.S. 3-month treasury bill, dating back from 2/1/1957 to 22/12/2011 (14342 observations). The series of the indices and of the 3-month treasury bill were retrieved from the U.S. Federal Reserve Bank.

Below are depicted all the price values (daily) for the Dow Jones index, the S&P 500 index and the 3-month treasury bill.

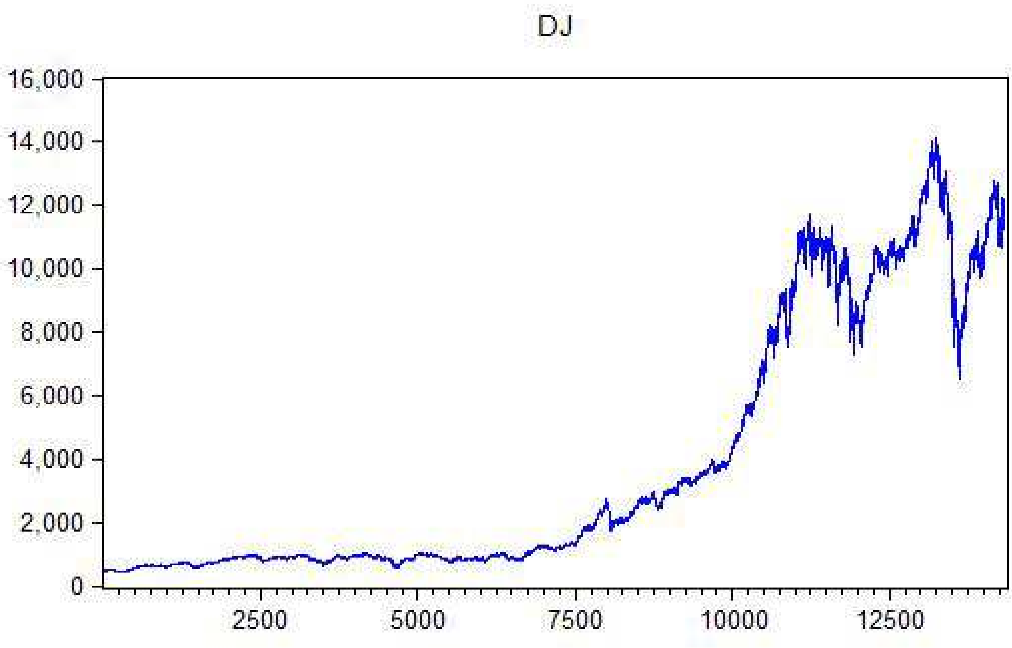


Figure 1: Dow Jones index (daily prices from 2/1/1957 to 22/12/2011)

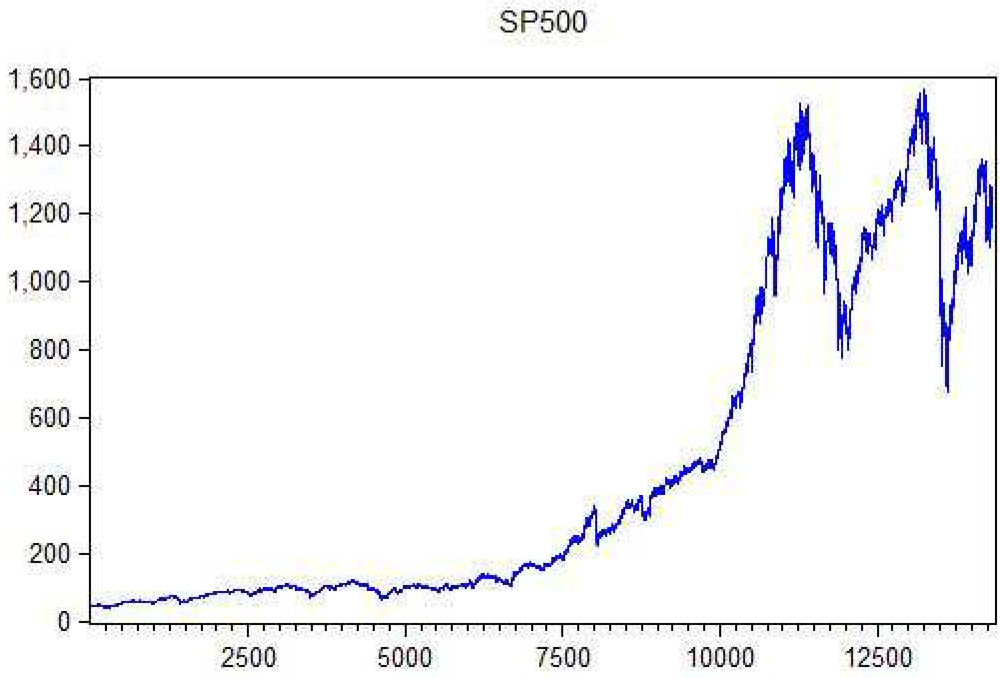


Figure 2: S&P 500 index (daily prices from 2/1/1957 to 22/12/2011)

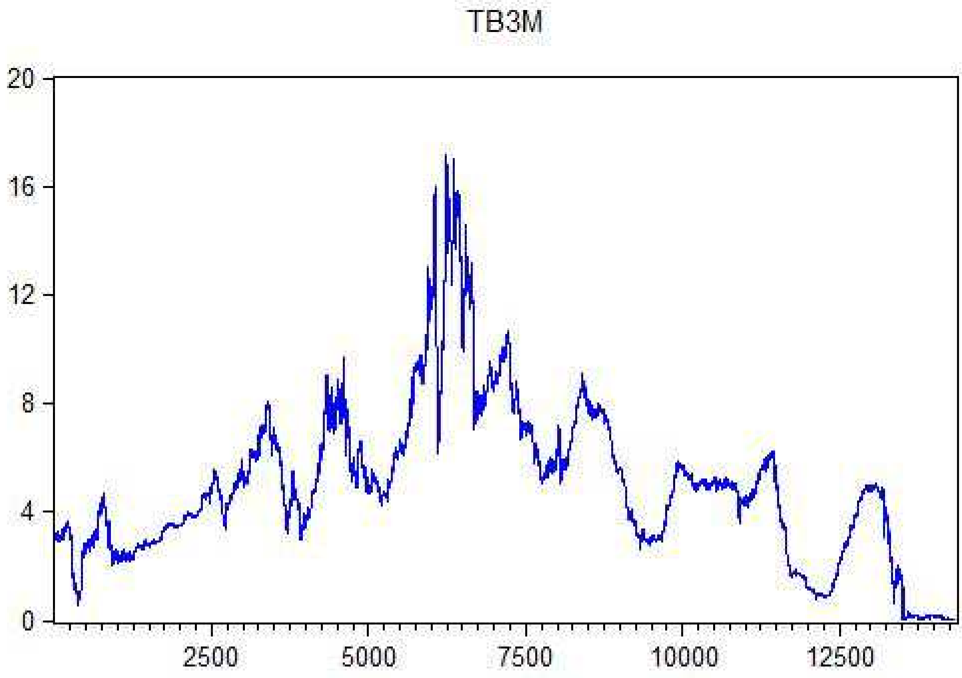


Figure 3: U.S. 3-month treasury bill (daily prices from 2/1/1957 to 22/12/2011)

2.3. Empirical testing

2.3.1. Dickey – Fuller test (ADF)

It is being observed that real financial time series often do exhibit the problem of 'non-stationarity' in their structure and it is regarded as affecting the regression coefficients due to biasness and invalidity of hypothesis testing.

In order to manage the problem of non-stationarity in time series, one needs to distinguish the relevant stationary process that the variables are involved to – i.e. whether they are non-stationary due either to trend (trend stationary process – TSP) or to differences (difference stationary process – DSP). Thus, in order to amend the estimated variables in the TSP process, one must entail time as a defining variable in the model, while in time series that exhibit the DSP process one must use the first differences of the various variables instead of real prices.

Finally, testing for non-stationarity in time series we utilize various unit root tests, one of them which is the Dickey-Fuller test and the Augmented Dickey Fuller test (1979) that allow for detecting both the TSP and DSP process.

2.3.1.1 Theoretical background of the DF test (Dickey-Fuller test)

One immediately obvious method to testing for unit roots would be to examine the autocorrelation function of the series of interest (Enders, 1995). However, even if shocks to a unit root process will remain indefinitely, the random walk process will fade away very slowly to zero. Therefore, particular testing techniques have been developed so as to control for these problems.

The basic objective of the test is to examine the null hypothesis that $\varphi = 1$ in $y_t = \varphi y_{t-1} + u_t$ against the one-sided alternative $\varphi < 1$. For this instance, the hypotheses of interest are:

H_0: series contain a unit root, versus

H_A: series is stationary

In practice, the following regression is employed, rather than the one above, for ease of computations and interpretation:

$$\Delta y_t = \gamma y_{t-1} + u_t$$

so that a test of $\varphi = 1$ is equivalent to a test of $\gamma = 0$ (since $\varphi - 1 = \gamma$).

The actual procedure of implementing the DF test involves several decisions. We note that a random walk process may have no drift or it may have one or it may have both deterministic and stochastic trends. To allow for the various possibilities, the DF test is estimated in three different forms, that is, under three different null hypotheses.

$$\textbf{Process 1: } \Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t$$

$$\textbf{Process 2: } \Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t$$

$$\textbf{Process 3}: \Delta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t$$

where *t* is the time or trend variable and y_t the logarithm of prices. In each case, the *null hypothesis* is that γ = 0; that is, there is a unit root—the time series is non-stationary. The alternative hypothesis is that γ is less than zero; that is, the time series is stationary. If the null hypothesis is rejected, it means that y_t is a stationary time series with zero mean in the first case, that y_t is stationary with a nonzero mean [= $\beta 1/(1 - \rho)$] in the second case and that y_t is stationary around a deterministic trend.

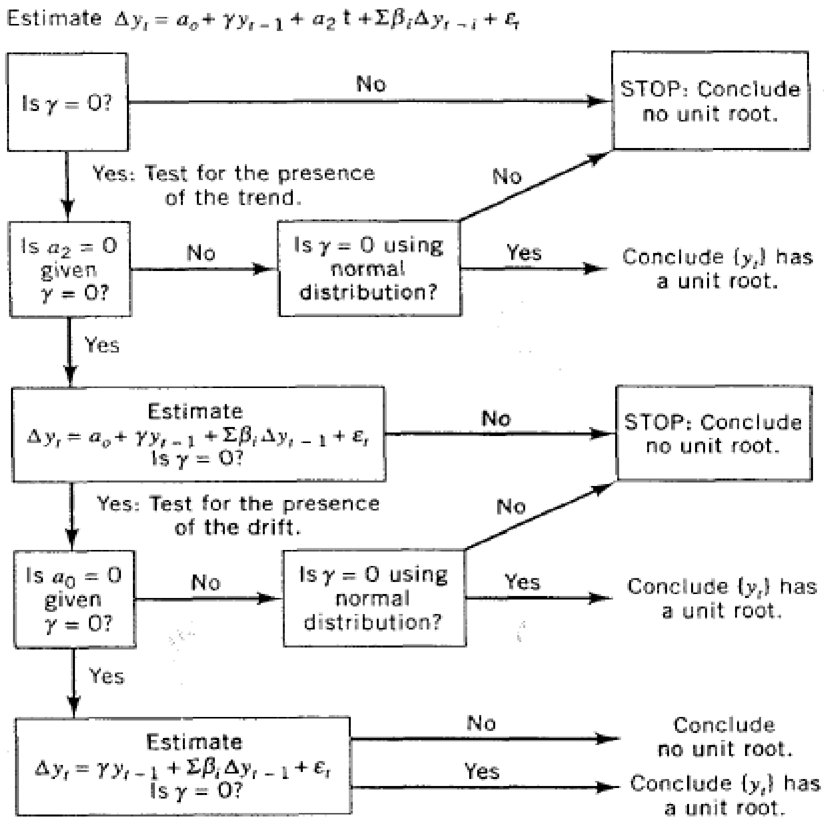
2.3.1.2. The Augmented Dickey-Fuller (ADF) test

The tests above are valid only if u_t is a white noise. However, u_t is assumed not to be autocorrelated, but would be so if there was autocorrelation in the dependent variable of the regression (Δy_t) which has not been modeled yet. If this would be verified, the test would be robust. One solution therefore is to 'augment' the test using *p* lags of the dependent variable. This could be written as:

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p} a_i \Delta y_{t-1} + u_t$$

The lags of Δy_t now absorb any dynamic change that is present in the dependent variable, to ensure that u_t is not autocorrelated.

Finally, below it is being presented in sort, the methodology that needs to be followed in order to test for the ADF statistic.



Source: Enders, 1995, pp. 259.

Figure 4: Augmented Dickey-Fuller statistic (methodology)

2.3.1.3. Empirical results – Augmented Dickey-Fuller test

We examine the three time series (Dow Jones, S&P 500, 3-month treasury bill) for the existence of a unit root. The first step is to check the statistical significance of all the ADF values and then we proceed by examining the hypothesis testing of the existence of a unit root for each one of them. The results are depicted below.

Table 1: Unit root results (logarithm of prices)

	Dow Jones		**S&P500**		**3M t-b**	
	t-stat	*prob.*	*t-stat*	*prob.*	*t-stat*	*prob.*
Process 1						
ADF (γ)	-1.799624	0.7052	-1.941076	0.6326	0.561235	0.9995
Trend (α2)	1.847561	0.0647	1.868551	0.0617	-1.901752	0.0572
Process 2						
ADF (γ)	-0.156853	0.9414	-0.525644	0.8839	1.361175	0.9990
Constant (α0)	0.544876	0.5858	1.081633	0.2794	-1.838750	0.0660*
Process 3						
ADF (γ)	2.678314	0.9984	2.618633	0.9981	-0.106709	0.6470

Statistically significant at 10* level

We begin the process step-by-step as it is being described in the figure above, by looking firstly at the Dow Jones results and particularly the ADF critical values as depicted in the table above. For *process 1*, we accept the $H_0 : \gamma = 0$ and we continue by checking the hypothesis $H_0 : \alpha_2 = 0 | \gamma = 0$. We compare the t-stat value of the coefficient α_2 with the corresponding critical value τ_c where $\tau_c = 2,78$ (τ_c is the modified value for the ADF distribution). So $\left|\tau_{\alpha_2}\right| = 1,85 < \left|\tau_c\right| = 2,78$, therefore we accept $H_0 : \alpha_2 = 0 | \gamma = 0$ and we continue with *process 2*, where we examine again the $H_0 : \gamma = 0$ (we accept the H_0) and we then examine the $H_0 : \alpha_0 = 0 | \gamma = 0$ where we again accept the H_0 and we end up by looking at the *process 3* by concluding that in the DJ series there is a unit root.

By following the exact same procedure we distinguish that the S&P 500 and the 3-month treasury bill series do exhibit unit root phenomena – i.e. the series are non-stationary, therefore in order to correct this problem we need to calculate new ADF values for the 1st differences of our series. The results are depicted below.

Table 2: Unit root results (1st differences)

	DLDow Jones		**DLS&P500**		**DL3M t-b**	
	t-stat	*prob.*	*t-stat*	*prob.*	*t-stat*	*prob.*
Process 3						
ADF (γ)	-86,53450	0,0001	-86,18628	0,0001	-19,52891	0,0001

We only look at the *process 3* results, since previously all the corresponding series exhibited unit root at this stage. We amend the values into 1st logarithmic differences and we observe that non-stationarity has been corrected (existence of I(1) series).

Below it is being depicted the returns of the corresponding time series where we can also confirm the results above.

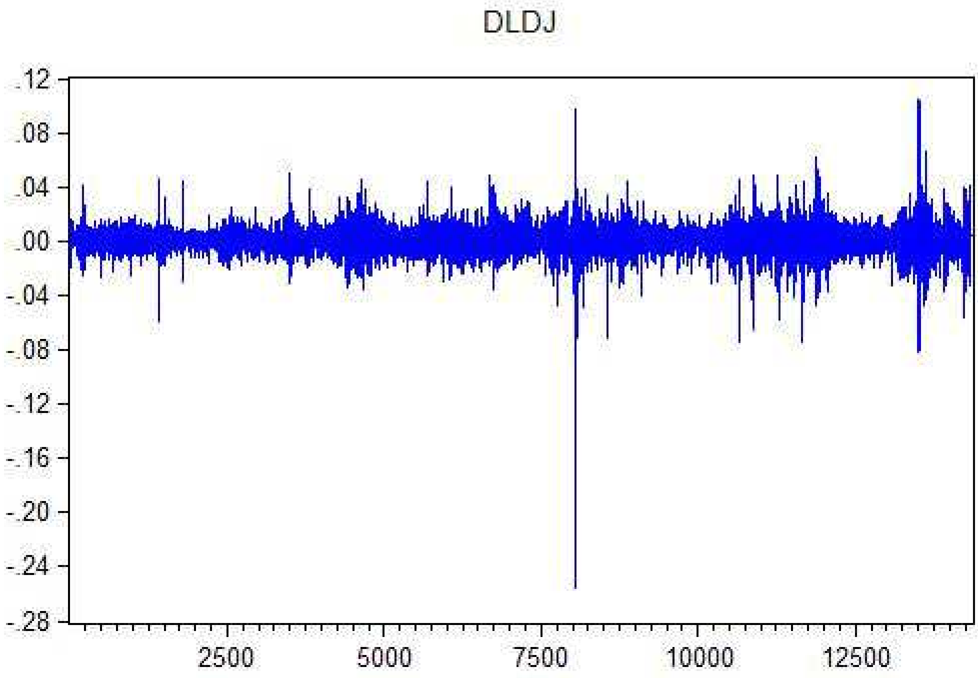


Figure 5: Dow Jones daily returns (02/01/1957-22/12/2011)

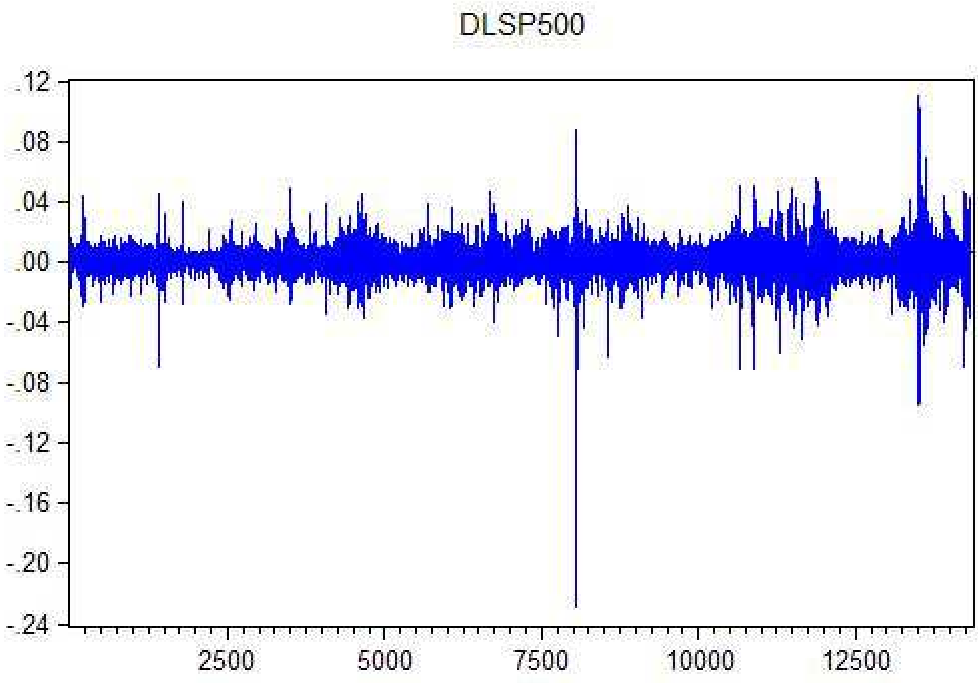


Figure 6: S&P 500 daily returns (02/01/1957-22/12/2011)

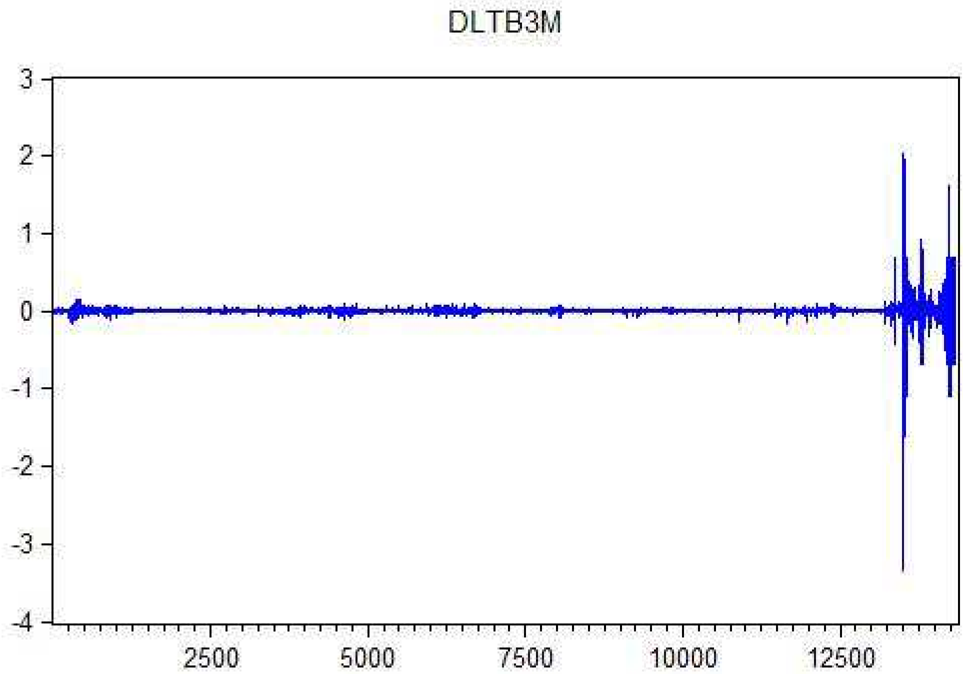


Figure 7: 3-month treasury bill daily returns (02/01/1957-22/12/2011)

2.4. Descriptive Statistics

Additional information can also be derived using particular statistics for testing departures from normality as the measures of Skewness and Kurtosis, as well as the correlogramms.

Skewness measures the extend to which a distribution is not symmetric about its mean value. Its mathematical formula is expressed as follows:

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{s\sqrt{\frac{N-1}{N}}}\right)^3$$

where N is the number of observations, y_i the values of corresponding variable, $\bar{y}$ the mean value of the relevant variable and s the standard deviation. Additionally, when the Skew-measure is larger than zero, the distribution is said to be right-skewed whereas when is it less than zero the distribution is referred as left-skewed. When its value is equal to zero, the distribution is symmetrical, i.e. the observations are distributed evenly around the mean.

Any deviations around this statistical measure can also give additional information with regards to the excess returns in the series that are mainly attributed to the way information is absorbed into prices. For this reason when we experience a bear market, usually the skewness measure is less than zero and in the bull market the other way round. For a market to be considered efficient, this measure must be equal or around zero.

Besides that, Kurtosis measures how fat the tails of the distribution are. A normal distribution is defined to have a coefficient of kurtosis equal to 3. However when this measure is over 3 the distribution is said to be leptokurtic meaning that has fatter tails and is more peaked at the mean while a platykurtic distributions (Kurt < 3) will be less peaked in the mean and will have thinner tails. In practice thought, a leptokurtic distribution is far more to characterize financial time series and to characterize the residuals from a certain model. The measure above can be expressed as:

$$Kurtosis = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \overline{y}}{s\sqrt{\frac{N-1}{N}}}\right)^4$$

Finally, the measure of Jarque-Bera (J-B) uses the property of a normally distributed random variable that the entire distribution is characterized by the first two moments-mean and variance. For skewness and kurtosis to be statistically significant, the value of the J-B test must be larger than 5,99 and its prob-value larger than 0,05.

Detailed analysis about the dataset in our study will be conducted in section 2.8.

2.5. The ARCH-GARCH models

In order to filter properly our data and come up with solid results, one needs to consider the variances of the error terms of the corresponding models and how they evolve throughout time. Data in which variances of the error terms are not equal are assumed to suffer from heteroscedasticity, meaning that the regression coefficients for an ordinary least squares regression are still unbiased while the estimated standard errors can become too narrow, giving a false impression about the model.

Instead of considering the above, an ARCH model (autoregressive conditionally heteroscedastic model) can treat heteroscedasticity as a variance to be modelled and controlled and was firstly being introduced by Engle (1982).

Prior to introducing the model it would be worthwhile to mention that the key issue in applied econometric models, like the ARCH model, is the accuracy of the predictions of the model itself and the way it helps to forecast future deviations from the mean value, in explaining for instance volatility-driven phenomena.

Following that, Engle (1982) proposed a model where a random variable y_t is drawn from a conditional density function $f(y_t | y_{t-1})$ with its first-order auto-regression being expressed as:

$$y_t = \gamma y_{t-1} + \varepsilon_t, \ \varepsilon_t \sim N(0, \sigma^2)$$

It was assumed that the model's variance is conditional and is expressed as a linear function of past squared errors leaving the unconditional one constant. A preferable model is:

$$y_t = \varepsilon_t h^{1/2}$$

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2$$

where h_t is the model's conditional variance and V(ε_t) = 1. In addition, when the model is of order q – that is ARCH(q) it can be expressed as:

$$h_t = VAR(e_t) = \alpha_0 + \sum_{j=1}^{q} \alpha_{t-q}^2$$

Following the above, Tsay (2005, p. 106) proposed some weaknesses that ARCH models exhibit which are summarized below:

- *The model assumes that positive and negative shocks have the same effects on volatility because it depends on the square of the previous shocks.*
- *It is rather restrictive and limits their ability to prevent excess kurtosis.*
- *It does not provide any new insight for understanding the source of variations of financial time series. It gives little information on what causes excess behaviour in variance.*
- *They are likely to overpredict volatility because they respond slowly to large isolated shocks to the return series.*

Bollerslev (1986) extended the previous work and introduced a more general class of processes, the GARCH model, allowing for a more flexible structure. Therefore, let ε_t denote a real-time stochastic process and ψ_t the information set throughout time t. The GARCH (p,q) process is the given by:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$
$$= \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t$$

where

$$p \geq 0,\ q > 0$$
$$\alpha_0 > 0,\ \alpha_i \geq 0,\ i = 1,\dots,q$$
$$\beta_i \geq 0,\ i\ =\ 1,\dots,p$$

The formula above asserts that the best predictor of the variance in the next period is the weighted average of the long-run average variances, the ones predicted for this period and the new information in this period that is captured by the most recent squared residual.

The common feature of ARCH and GARCH models is that they specify the conditional variance as a function of the past shocks so as volatility can evolve over time. The distinction between these two methodologies is that while ARCH incorporates a limited number of lags in derivation of the conditional variance, GARCH allows all lags to exert an influence by including the past value of the conditional variance itself, in addition to the past values of the squared errors.

2.5.1. The ARCH-M model

The ARCH-M model is an extension of the classical ARCH model, allowing for the conditional variance to affect the mean. It was firstly introduced by Engle *et al.* (1987) in their study on U.S. treasury bills and corporate bonds.

The basic formulation of the model itself suggests that the excess stock returns depend on a constant term and on the uncertainty of the excess return (risk premium[5]), namely:

$$ER_t = \beta + \delta\sigma_t^2 + e_t,\ e_t \sim N(0,\sigma^2)$$

with the corresponding variance being formulated as:

$$\sigma^2 = \alpha_0 + \alpha_1 \sum_i w_i e_{t-i}^2$$

where it is a definite function of the information available to investors and the ARCH process implies that the most useful information is a weighted sum of the previous period surprises e_t.

Bottazzi and Corradi (1991) in their research in the Italian stock market from January 1980 to April 1989, using an ARCH-M specification model and a non-parametric analysis found that there is evidence of ARCH effect in their time series with a relevant time-varying risk premium process. Specifically, when an additional regressor was introduced

[5] According to Engle *et al.* (1987, p. 392) risk premium is defined as ‘the compensation that risk-averse economic agents require for holding risky assets and is measured by the variance of the returns from holding the asset and the compensation by a rise in the expectation of the return’.

(acceleration of inflation rate) the time-varying risk premium was getting even more statistically significant. They included other potential variables in the expression of the conditional variance:

$$\sigma^2 = \alpha_0 + \alpha_1 \sum_i w_i e_{t-i}^2 + \varphi Z_t$$

where Z_t represents a set of variables that could help estimate higher volatility in the model, in an anticipation that φ is always statistically significant.

An important point to mention is that in general ARCH/GARCH-M models portray a fundamental trade-off relationship between expected returns and the volatility measure (σ^2), with the coefficient δ capturing the dynamic pattern of the changing risk premium over time, therefore bringing this theoretical framework closer to the well-known models of CAPM and APT in which *ex-ante* returns are related to the conditional variance of returns.

2.6. Detecting positive feedback by using a univariate noisy Mackey-Glass (MG) model

Mackey and Glass (1977) in their study developed a discrete version of the deterministic MG model, whereas based on its basic features Kyrtsou and Terrazza (2003) added a noisy term (white and heteroscedastic) in its primary version, in order to explain better various complex dynamics in financial time series.

Specifically it is being presented below:

$$X_t = \alpha \frac{X_{t-\tau_1}}{1 + X_{t-\tau_1}^{c_1}} - \delta X_{t-1} + \varepsilon_t, \ \varepsilon_t \sim N(0,1)$$

where α and δ are parameters to be estimated, τ is the delay and c a constant. Maximum likelihood tests are employed in order to choose the best delay factor, as different values of τ and c create dynamic changes in the whole process.

In theory, positive feedback effects are being detected when the sum of $(\alpha - \delta)$ and $(\alpha - \delta)$ is positive (irrational trading) while when the corresponding sum is negative then negative feedback behaviour is apparent (rational trading).

2.7. The model

The aim of the study is to examine the effect of risk-premium and feedback trading on excess stock returns in the U.S. and specifically in the Dow Jones and S&P 500 indices during a period from 02/01/1957 to 22/12/2011. The newly developed model encompasses characteristics from both the ARCH (Engle, 1982) and GARCH models (Bollerslev, 1986) and a univariate noisy Mackey-Glass one (Mackey and Glass (1977), Kyrtsou and Terraza, 2003). The general formula is the one below:

$$ER_t = c + \delta\sigma_t + a\,\frac{ER_{t-\tau}}{1+ER_{t-\tau}^2} - \gamma ER_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2)$$
$$\sigma_t^2 = \mathrm{a}_0 + \mathrm{a}_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where, ER_t denotes the expected return at time t, τ = 1, $\delta\sigma_t$ denotes the risk-premium modeled as a positive function of the conditional standard deviation of a stock price, ER_{t-1} is referred to the expected return at time t-1 and the term $\frac{ER_{t-1}}{1+ER_{t-1}^2}$ denotes the non-linear nature of the series. Positive feedback effects are realized when ($a-\gamma$) gives a positive result, whereas negative feedback gives out a negative ($a-\gamma$) result. Moreover, σ_t^2 is the conditional variance of the returns at time t, e_{t-1}^2 is the innovation at time t-1 and a_0, a_1 and β_1 are non-negative fixed parameters.

The model allows for excess returns ER_t to be determined by the risk-premium $\delta\sigma_t$ and the corresponding feedback trading strategies captured under $\left[a\,\frac{ER_{t-1}}{1+ER_{t-1}^2} - \gamma\, ER_{t-1}\right]$.

We note that the trade-off coefficient δ was interpreted as a relative risk aversion by Merton (1980) whereas Engle et al. (1987) proved that the sign and the magnitude of this parameter depends solely on the utility functions of the agents and the supply conditions of the corresponding assets. Hence, based on these characteristics, δ can take a positive, a negative, or a zero value. As a consequence when δ is statistically significant σ_t contributes to the risk premium so that the premia can differ between periods of relative stability or instability.

2.8. Data analysis

2.8.1. Descriptive Statistics – Sample from 02/01/1957-22/12/2011

In our study the descriptive statistics results for the Dow Jones returns, the S&P 500 returns and the 3-month treasury bill returns for the corresponding period (02/01/1957-22/12/2011) are depicted below (Table 3). For further information see at Tables A.1.-A.3. (Appendix) with the corresponding histograms.

Note that in order to calculate the returns we use the natural logarithms of the particular time series:

- Dow Jones index (Returns): $dldj = \ln(dj) - \ln(dj(-1))$,
- S&P 500 index (returns): $dlsp500 = \ln(sp500) - \ln(sp500(-1))$
- 3-month treasury bill (Returns): $dltb3m = \ln(tb3m) - \ln(tb3m(-1))$

Table 3: Descriptive statistics – daily stock returns (period 02/01/1957-22/12/2011)

	DLDJ	DLSP500	DL3MTB
Skewness	-1,26	-1,04	-2,63
Kurtosis	42,10	32,01	438,28
Jarque-Bera	917560,2	505743,1	1,13E+0,8
Prob.	0,0000*	0,0000*	0,0000*

*: statistically significant at 5% level (critical value)

As it can be concluded all the three time series exhibit negative asymmetry (left-skewed) implying that there is not a smooth absorption of information into prices, since heterogeneous agents seem to trade within the markets. On the other hand the Kurtosis measure is far beyond the typical value (K >3) suggesting that our data follow a leptokurtic distribution and possibly heteroscedasticity might be apparent in the series. The higher the value of Kurtosis, the more volatile variance in our series is apparent, suggesting possible speculative phenomena that need to be examined separately. Finally the J-B statistic measure confirms that the above results are correct and rejects the normality hypothesis.

Bearing in mind the high-degree of volatility that is evident in the series as well as the various financial phenomena-crises that took place during the studied period, one needs to consider an alternative approach in order to examine better the series and come up with robust results.

We consider one of the most striking events that took place in the late 1990s the Dot-Com bubble in the U.S. when the NASDAQ index plummeted in one day (10/03/2000) from 5.132,52 to 5.048,62. Even if the bubble was grossly overvalued (DeLong and Magin, 2006), still influenced significantly world financial markers. For this reason we divide the sample into two parts, where the first one is dating back from 02/01/1957-09/03/2000 (pre Dot-Com bubble era) and the second one from 10/03/2000 to 22/12/2011 (post Dot-Com bubble era).

2.8.1.1. – The pre Dot-Com era (period 1 from 02/01/1957 to 09/03/2000)

Below we provide the descriptive results with regards to the pre Dot-Com period for the corresponding returns and excess returns in the financial series.

Table 4: Descriptive statistics – Daily Stock Returns (02/01/1957-09/03/2000)

	DLDJ_1	DLSP500_1	DL3MTB_1
Skewness	-2,112662	-1,823645	-0,335505
Kurtosis	67,51018	53,22793	16,8306
Jarque-Bera	1961888	1190530	90051,3
Prob.	0,0000*	0,0000*	0,0000*

*: statistically significant at 5% level (critical value)

We indicate that the first dataset of our series still reveals negative asymmetry (left-skewed) with the kurtosis value well above the standard one (K>3) indicating rather high volatility especially in the series of Dow Jones and S&P 500, while the Kurtosis from the 3-month TB is relatively low in absolute terms ($K_{3m\text{-}TB}$ = 16,8306). The Jarque-Bera measure is statistically significant (prob. value = 0,000 < 0,05).

Table 5: Descriptive statistics – Daily Stock Excess Returns (02/01/1957-09/03/2000)

	EXDJ_1	EXSP500_1
Skewness	0,172497	0,177002
Kurtosis	12,17497	11,88058
Jarque-Bera	39571,36	37079,22
Prob.	0,0000*	0,0000*

*: statistically significant at 5% level (critical value)

Contrary to what mentioned above, the excess return series exhibit completely different results. Skewness is found to be positive (right-skewed) which means presence of fat-tails in the distributions signifying positive returns, whereas the kurtosis measure for both the series is presented pretty low (in absolute terms) indicating that there is an element that influences the calculation of excess returns and possibly it is the 3-month treasury bill and its ups and downs. Note that excess returns are calculated as:

$$ex_i = dl_i - dltb3m$$

where *i* stands for either Dow Jones or S&P 500 indices.

2.8.1.2. – The post Dot-Com era (period 2 from 10/03/2000-22/12/2011)

Below we provide the descriptive results with regards to the post Dot-Com period for the corresponding returns and excess returns in the financial series.

Table 6: Descriptive statistics – Daily Stock Returns (10/03/2000-22/12/2011)

	DLDJ_2	DLSP500_2	DL3MTB_2
Skewness	-0,031661	-0,147778	-1,247079
Kurtosis	10,59225	10,53786	100,1492
Jarque-Bera	7383,532	7297,29	1208856
Prob.	0,0000*	0,0000*	0,0000*

*: statistically significant at 5% level (critical value)

Even if in the second period there are fewer observations (3073 observations contrary to 11269 ones in the first sub-period) we still realize that the returns of the series are said to be left-skewed (negative skewness) contrary to period 1. The kurtosis measure is lower in absolute terms for the series of Dow Jones and S&P 500 while for the 3-month treasury bill exceeds its value ($K_{3m\text{-}TB}$ = 100,1492).

Table 7: Descriptive statistics – Excess Daily Stock Returns (10/03/2000-22/12/2011)

	EXDJ_2	EXSP500_2
Skewness	1,134421	1,114059
Kurtosis	98,56943	98,30308
Jarque-Bera	1170511	1163975
Prob.	0,0000	0,0000

*: statistically significant at 5% level (critical value)

As depicted in the table above (excess returns), for the second period the kurtosis value is presented too high indicating that excess volatility in our data is apparent leading to speculative phenomena, due to interaction of different agents. Skewness measure is depicted as positive (right-skewed) and the Jarque-Bera statistic (prob.=0,000) confirms that the distribution of our data deviates significantly from normality.

Finally, looking at the autocorrelation figures of the excess returns (see Appendix Figures 1-6) one can conclude that there is no a certain pattern of positive or negative autocorrelations, rather than there is an interchangeable trend indicating the heterogeneous nature of agents that are involved in the system. Autocorrelation statistics are highly significant and the discontinuous pattern observed is attributed to the mixture of short and long memory components that the corresponding time series exhibit. The phenomenon of this transposable correlation in time series is often found in literature as 'the anti-persistent behaviour' in time series and was primarily developed in Physics in the seminal work of Mandelbrot and Wallis (1968, 1969b).

This behaviour has also been called the "Noah effect" in which exceptionally large amplitudal surges taking place in a given stochastic process. The Noah effect is exhibited by stationary stochastic processes with heavy tailed stationary levels (Eliazar and Klafter, 2006). However the examination of the exact autocorrelation pattern, in the corresponding series, lies outside the purpose of this research, therefore we will limit our scope into just mentioning it only.

2.8.2. Descriptive statistics – Discussion

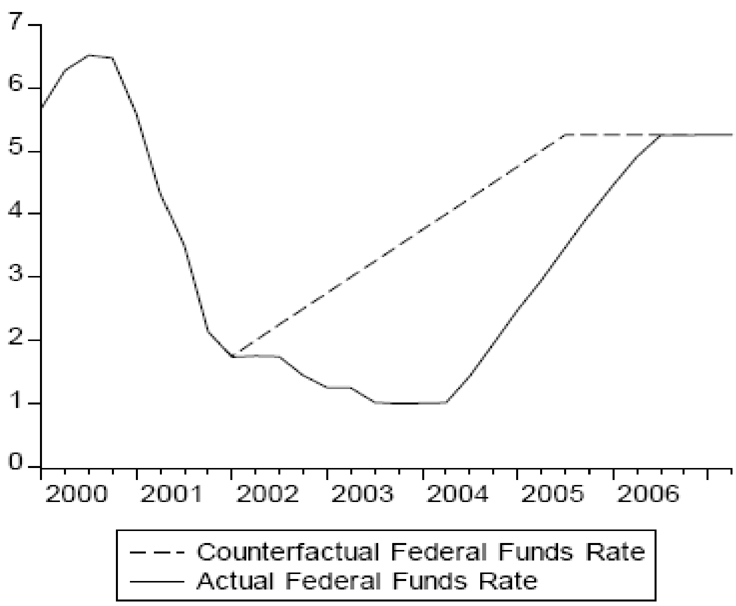
As we concluded from the analysis above, the descriptive statistic outcomes reveal some significant results about the nature of the data and the way shocks and crises are detected in the examined period. We mostly observe leptokurtic returns and excess returns (excess kurtosis-'fat-tails'), combined with asymmetric fundamental information that is captured under the skewness measure. Price series tend to develop differently due to varying information as trading in some periods might be slow and in some other ones might be intense and excessive. As it can be seen from the return figures, volatility clustering is evident, justifying the switching behaviour between different investment strategies (fundamentalist and chartist trading).

Lux and Marchesi (1999,2000) and Brock and Hommes (1998) find similar results indicating that once a certain tactic of chartists is exceeded, the system becomes unstable and extreme returns occur, as prices deviate significantly from fundamental values creating bubbles and crashes. Herding phenomena become apparent and positive feedback strategies are activated. These two seminal stylized facts of financial time series (volatility clustering, fat-tails) are the most common ones observes when examining heterogeneous agent models.

In our dataset however, we focus the analysis solely on the excess returns as they contribute the most in the model, since we examine the effect that risk premium and feedback trading have on them. Taking a good look at the results, for both the periods, we conclude that for period 2 excess kurtosis is realized compared to period 1 where we would expect this to happen as the pre Dot-Com era was the most volatile one (see return series for period 1). We then need to consider that in order to calculate excess returns ($ex_i = dl_i - dltb3m$) we utilize the return on the 3-month treasury bill as a parameter signifying that major changes in it might well affect the value of excess returns. It is obvious that this ‘anomaly’ in excess return results indicates that short-term interest rates played a significant role during the two periods.

Going forward, it is a common knowledge that when imposing either a loose or strict monetary policy, interest rates are a vital source for controlling the economy. Many researchers focused their studies on the recent financial crisis that begun in 2008 from the U.S. and developed shortly in the whole world, indicating that macroeconomic policies and poor bank regulatory framework contributed the most in the contagion of the financial instability (Blundell-Wignall et al., 2008).

As John Taylor (Taylor, 2009) shows, U.S. monetary policy since 2002 has been too expansionary. This verdict is based on an analysis of the federal funds rate. For more than 20 years the Federal Reserve has steered this interest rate and made changes in it in response to changes in the course of inflation and aggregate income. The Fed has raised (lowered) the federal funds rate when inflation and GDP growth have increased (decreased). The key point to this reaction (the so-called ‘Taylor rule’) was that the actual federal funds rate since 2002 has followed a course markedly below what this policy rate should have been according to the Taylor rule and as depicted below.



Source: Taylor, 2007, p. 3

Figure 8: Loose fitting

As a result, interest rates remained low at a very long period reducing borrowing costs and accelerating the housing boom that took place in the late 2006. After the Dot-Com bubble and the 9/11 terrorist attack in New York, the U.S. Federal Reserve decreased short-term interest rates (2000-2003) by far, in an attempt to give boost to the real economy and house prices, thus making subprime lending easier for everyone. As a result low income families could have the opportunity to obtain house loans very easily. However, it did not take too long for the Federal Reserve to change policy by affecting the adjustable-rate mortgages (ARMs) and consequently private demand.

Above all and contrary to what mentioned before, Bernanke (2010) in his speech claimed that if one considers the information available at the time (and especially current estimates of the output gap) monetary policy was not overly expansionary and played, at most, a modest role in the U.S. housing bubble. In his view, financial regulatory policy should be the appropriate tool for preventing harmful asset price bubbles in the future.

Additionally, Taylor (2008) argued that the low interest rates in 2002-2004 were caused by global factors beyond the control of the monetary authorities. The interest rate decisions by the monetary authorities were not the major factor causing the boom. However appealing this might sound, long term interest rates remained low for a while even after the short-term federal funds rate started increasing. Taylor referred to the excess of world saving - a global saving glut (i.e. the world saving as a fraction of world GDP) - which pushed interest rates down in the United States and other countries. Interestingly he argues that mere empirical evidence occur to support this view.

Furthermore, Bordo (2008) comments that the rising policy on interest rates triggered much of the recent financial crisis and its main causes were the changes in regulation and the ‘relaxed’ lending standards that combined with abnormally low interest rates led to an uneven financial turmoil.

Summing up, it is true that monetary excesses and loose government intervention along with financial institution’s small regulation led to a distrefull position both investors and individuals. Real short-term interest rates were mush influenced in the U.S. imposing an immediate effect on equity excess returns.

2.9. – Empirical Findings on Risk Premium and Feedback Trading effects - Discussion

Moving forward, this section will cover the analysis of the empirical findings deployed under the use of the GARCH-M technique and the univariate noisy Mackey-Glass model. Initially we examine whether δ (risk-premium) is statistically significant so as to proceed further in order to detect feedback trading effects. We do so by estimating a simple (G)ARCH-M (6,0) model by getting the results depicted in Table 8 (next page).

For the Dow Jones index (period ranging from 02/01/1957 to 22/12/2011) as well as for the same index and the S&P 500 during the sub-period ranging from 10/03/2000-22/12/2011, the coefficient δ, describing the relationship between risk and return, is found to be negative and statistically significant and varies in magnitude across the three dimensions. The t-stat for the null hypothesis of $\delta=0$ is rejected in all three cases at the 5% and 10% levels. The implication of this finding is that the risk premia are said to be index specific in magnitude and display an adverse risk-return trade-off over time.

As mentioned above, the sign of δ depends on the investors' utility functions and as discussed earlier, we are dealing within a market with heterogeneous characteristics where investors' demand for equities differs along with their expectations. Even in the entire-period sample or even in the sub-period one would expect a positive sign of δ, justifying the fact that the more volatile the market is, the higher expected returns in equities are realized signifying speculative phenomena with high risk.

Nonetheless, in our study δ is negative, implying that less investors are willing to invest/trade in stocks and prefer to save. However, this seems a bit odd while trading and speculative phenomena in both the periods, the entire one and the one that succeeded the Dot-Com bubble, were intense. Interestingly though, Glosten et al. (1993) in their study on value-weighted NYSE stocks between April 1951 to December 1989, found a negative relation between conditional monthly expected return and variance using a GARCH-M model, a research consistent with our study. They offered two reasons for this; first riskier periods may coincide with periods when investors are able to bear risk and second, if investors want to save more during riskier times and all assets are risky, competition may raise asset prices and lower risk premia. We proceed then with the joint estimation of risk premium and Mackey-Glass terms in order to indentify possible impacts of a nonlinear feedback into the excess returns and their risk premium as well.

Table 8: Estimates for the (G)ARCH-M (p,q) model for the Dow Jones and S&P 500 indices for the whole period and for each sub-period.

	c	δ	a_0	a_1	a_2	a_3	a_4	a_5	a_6	β_1
EXDJ	**0,001174 (0,0097)***	**-0,072866 (0,0252)***	**4,85E-0,6 (0,0004)***	**0,157922 (0,0085)***	-	-	-	-	-	**0,856721 (0,0000)***
EXSP500	0,001027 (0,0109)*	0,001747 (0,8766)	4,85E-0,6 (0,0002)*	0,165849 (0,0039)*	-	-	-	-	-	0,852387 (0,0000)*
EXDJ_1	0,000566 (0,0791)**	-0,023885 (0,3270)	2,05E-0,6 (0,0001)*	0,069671 (0,0000)*	-	-	-	-	-	0,926796 (0,0000)*
EXSP500_1	0,000462 (0,1253)	-0,014546 (0,5338)	1,90E-0,6 (0,0002)*	0,071164 (0,0000)*	-	-	-	-	-	0,926168 (0,0000)*
EXDJ_2	**0,006387 (0,0177)***	**-0,420759 (0,0041)***	**9,31E-0,5 (0,0355)***	**0,464002 (0,0434)***	**0,240993 (0,0217)***	**0,095940 (0,0615)****	**0,070357 (0,0953)****	**0,238643 (0,0001)***	**0,340856 (0,0008)***	-
EXSP500_2	**0,007144 (0,0325)***	**-0,441819 (0,0088)***	**0,000115 (0,0757)****	**0,437302 (0,0551)****	**0,260130 (0,0183)***	**0,083942 (0,0264)***	**0,062826 (0,1125)****	**0,267788 (0,0000)***	**0,265017 (0,0000)***	-

Probability is given within the parentheses;
*: Coefficient statistically significant at 5% level;
**: Coefficient statistically significant at 10% level

Below are presented the empirical testing results with regards to feedback trading effects on excess returns for both the indices (Table 9).

Similar to Table 8, we are interested only in the time periods where δ is statistically significant. Therefore the variables of interest are EXDJ, EXDJ_2 and EXSP500_2. Notably though, we observe that the variable EXSP500, after having filtered the data properly and having introduced the non-linear terms, it turns out to be statistically significant (prob.= 0,0467), contrary to the results under the GARCH-M model (see Table 8).

We begin by looking at the coefficients describing the conditional variance process – i.e. a_0, a_1 and β_1 for the *EXDJ variable*. All of them are highly significant suggesting that current volatility is a function of last period's squared innovation. Additionally a_1, in absolute terms, is less than β_1 ($a_1 = 0{,}157168 \langle \beta_1 = 0{,}858251$) implying that innovations have greater impact on volatility, than *vice versa*. The GARCH-M effect (parameter δ) is statistically significant and the parameters testing for the presence of feedback – i.e. γ and a are also statistically significant. Looking at the MG coefficients that describe feedback effects and calculating their sum $\left[a - \gamma = 1{,}109448 - (-1{,}011057) = 2{,}120505\right]$ we end up at low positive non-linear feedback relationship.

Moreover, for the *EXDJ_2* and *EXSP500_2* variables we again find a statistically significant negative risk premium coefficient while looking at the feedback effects we conclude that positive feedback trading occurs in both indices.

Comparing the values of risk premium (Table 8: $\delta_{EXDJ} = -0{,}072866$, $\delta_{EXDJ\_2} = -0{,}420759$, $\delta_{EXSP500\_2} = -0{,}441819$ contrary to Table 9: $\delta_{EXDJ} = -0{,}071432$, $\delta_{EXDJ\_2} = -0{,}423576$, $\delta_{EXSP500\_2} = -0{,}434948$) taken from the simple GARCH-M model and our proposed version we can understand that the inclusion of nonlinear feedback structure does not affect the significativity and values of δ.

Table 9: Estimates for the (G)ARCH-M-MG (p,q) model for the Dow Jones during the entire period and each sub-period as well.

	c	δ	γ	a	a_0	a_1	a_2	a_3	a_4	a_5	a_6	β_1
EXDJ	**0,001109 (0,0128)***	**-0,071432 (0,0300)***	**-1,011057 (0,0145)***	**1,109448 (0,0048)***	**4,56E-0,6 (0,0003)***	**0,157168 (0,0094)***	-	-	-	-	-	**0,858251 (0,0000)***
EXSP500	**0,000984 (0,0158)***	**-0,063134 (0,0467)***	**-1,004084 (0,0132)***	**1,106462 (0,0040)***	**4,23E-0,6 (0,0002)***	**0,163871 (0,00430)***	-	-	-	-	-	**0,854738 (0,0000)***
EXDJ_1	0,000430 (0,1815)	-0,016881 (0,4951)	-9,022503 (0,0868)**	9,173069 (0,0820)**	1,95E-0,6 (0,0055)*	0,067651 (0,0000)*	-	-	-	-	-	0,928767 (0,0000)*
EXSP500_1	0,000329 (0,2713)	-0,008097 (0,7325)	-10,75862 (0,0471)*	10,92062 (0,0442)*	1,80E-0,6 (0,0018)*	0,069539 (0,0000)*	-	-	-	-	-	0,927800 (0,0000)*
EXDJ_2	**0,006456 (0,0144)***	**-0,423576 (0,0033)***	**-0,523377 (0,0228)***	**0,515025 (0,0061)***	**9,35E-0,6 (0,0357)***	**0,469837 (0,0327)***	**0,228688 (0,0152)***	**0,097471 (0,0457)***	**0,071218 (0,0916)****	**0,240469 (0,0001)***	**0,340039 (0,0003)***	-
EXSP500_2	**0,007780 (0,0080)***	**-0,434948 (0,0007)****	**-0,856733 (0,0008)**	**0,836433 (0,0015)***	**0,000128 (0,0639)****	**0,435568 (0,0411)***	**0,231862 (0,0225)***	**0,102763 (0,0148)***	**0,205489 (0,0103)***	**0,449265 (0,0000)***	-	-

Probability is given within the parentheses;
*: Coefficient statistically significant at 5% level;
**: Coefficient statistically significant at 10% level.

So far and in a theoretical framework, we considered risk premiums as indicators of economic conditions; however it seems that they can directly affect the real economy. For instance, a decline in risk premia has played a significant role in the post Dot-Com period and triggered the housing bubble that exploded in 2008 in the U.S. Also they act as indicators to individuals' spending as they help them form their decisions. We consider the turnaround in equity markets from 2000 to 2003 when real interest rates were pulled back in order to control the economy. In addition, risk premia are also an important tool for monitoring the financial stability in system. Effective monetary policies can drive properly investors' sentiment toward risk and return and reward them accordingly. Fuerst (2006) in his study on a three-factor model that was firstly developed by Fama and French (1993), indicates that a rise in this risk premium affects the real economy through its impact on the investment decisions of small firms similar to the credit channel mechanism of monetary policy transmission , thus influencing directly the relative business cycles.

Since the proposed model and research are new, there are hardly any empirical studies combining the examination of the two variables (risk premium and feedback trading) therefore an attempt will be made to justify their relationship as close as possible.

Initially, Saunders and Yourougou (1990) and Yourougou (1990) examine the effect of interest rate changes on bank and non-bank firms during periods of relative interest rate stability (pre-October 1979) and high interest rate volatility (post-October 1979) and report that interest rates vary substantially overtime. Specifically, Yourougou (1990) argues that, during the period of interest rate stability, interest rate sensitivity was low and insignificant for bank and non-bank enterprises, while in the post-October 1979 period, interest rate risk demonstrated a significant impact on common stocks of financial intermediaries. They use simple OLS regressions indicating that interest rate risk is priced solely by capital markets and their empirical results reveal that interest-rate risk contributed incrementally to the expected returns of common stocks during the post-October 1979 period. Such results were not observed in the pre-October 1979 period, except for a subset of banks characterized by high but stable interest-rate sensitivity.

Elyasiani and Mansur (1998) suggest that applying time-varying models in financial stock series is very much helpful as shifts in monetary policies, as well as, financial and technological innovation might induce further changes into risk premia. They also mention that indifferent monetary regimes are crucial in determining that return process and their empirical findings suggest that the long-term interest rate has a negative and significant impact on the bank stock return. Likewise in our study, it is being implied that monetary decisions after the Dot-Com bubble and during the housing bubble in 2008 have significantly influenced short-term interest rates by affecting directly risk premia and in return the stock excess returns.

Turner *et al.,* (1989) provide evidence, under a Markov mean-variance model, in which risk premia estimates do not support an increasing trend. The estimated parameters indicate that agents ask for a higher return over T-bills in order to hold a risky asset in low-volatility periods and that the risk premium declines as the level of risk increases and is of negative sign as well. Their results are also consistent with French, Schwert and Stambaugh (1987).

Moving forward, our results reveal positive feedback trading effects that can be attributed to various strategies such as stop-loss orders, portfolio insurance and margin call-induced selling (liquidation of assets). By definition these strategies lead to sell decisions during market declines thus we would expect greater feedback activity during down markets, as it is widely mentioned in Koutmos (1997), Koutmos and Saidi (2001). Both studies indicate that negative first order autocorrelations are realized which become more negative as the market's volatility level rises. In our study positive feedback effects are evident in a high volatile period (kurtosis >> 3) that succeeded after the Dot-Com and housing bubbles. On top of that Sentana and Wadhwani (1992) argue that intensified positive feedback trading during bear markets can be rationalized by models where risk-aversion declines rapidly with wealth, a finding in line with the evidence of our research.

When agents have heterogeneous beliefs, the market reacts in a certain way in order to absorb the implications of their interactions, thus excess volatility and mispricing might well occur in the aftermath. Positive feedback strategies tend to destabilize the markets as new information is introduced in the system. Sornette (2003) provides an autopsy of the most significant bubbles that occurred worldwide during the past decades in which he refers to the Dot-Com crash as the one that was triggered by the 'network effect'. He claims the fact that positive feedback stems from economies of scale – i.e. keep costs down so as to take advantage of the opportunities that might rise in the economy. As hi-tech users become more and more, dot.com companies manage to lock their customer base thus enriching their excess returns. This positive feedback cycle (user growth) corresponds to further expected future earnings and future capital gains rather than present financial stability and reality.

Nonetheless, our empirical findings do not provide further information on the grounds of examining the exact relationship between risk premium and positive feedback trading as an ‘anomaly’ in the risk-free rate, that is captured under the excess returns, prevented us from inferring further results. The negative sign of δ, could possibly be attributed to less trading on new information if gains due to trading are lower than information and transaction costs. However, positive feedback traders are engaged in the market, even if risk premia are lower, anticipating a further improvement. We cannot entirely ignore the hypothesis of anti-persistent autocorrelation of excess returns although additional econometric testing needs to be utilized to investigate the problem, that lies outside the aim of this study.

Conclusion

The aim of this study is to empirically examine the effects of risk premium and positive feedback trading on excess returns in two major U.S. stock indices, the Dow Jones and the S&P 500 from 02/01/1957 to 22/12/2011. It proved to be clear that the exercise of a certain monetary policy can well influence equity excess returns and policy makers should not confuse institutional investors with traders in forming their decisions.

Linear analysis tools cannot always justify various financial phenomena thus non-linear analysis should be provided. In particular, the empirical results, based of a newly modified GARCH-M model – called GARCH-M-MG model, have provided various outcomes. Nevertheless, it needs to be mentioned that during the period of study, the world economy confronted numerous financial crises, from exchange rates crises to crude oil bubbles, yet it has been chosen as the most volatile period the Dot-Com bubble (10/03/2000) in order to divide the dataset into two parts and examine separately the forementioned.

There have been employed unit root tests (Augmented Dickey-Fuller test) so as to examine the stationarity in data and a GARCH-M model is used to absorb any heteroscedasticity causes. Additionally data are filtered further under the new model (GARCH-M-MG) as a non-linear factor is introduced capturing the feedback effects.

Empirical analysis proved that an ‘anomaly’ detected in the risk-free rate (negative risk premium), appears as a plausible justification of the negative sign in the risk premium coefficient during a period where the opposite behaviour would be expected (i.e. positive coefficient). Achieving positive feedback dynamics does not seem to affect the risk premium value. It only affects the excess returns of the series. Therefore, we encourage future empirical studies to look at this issue.

We cannot call for any further but to the use of alternative econometric models (TGARCH, EGARCH) and possibly to a structural break analysis by sub-dividing the data into further subsamples and examining the effects in more detail. Finally further tests with regards to the autocorrelation of returns need to be performed as the phenomenon of ‘anti-persistency’ is evident.

APPENDIX

Table A.1.: Dow Jones (Daily Stock Returns) – descriptive statistics results (02/01/1957-22/12/2011)

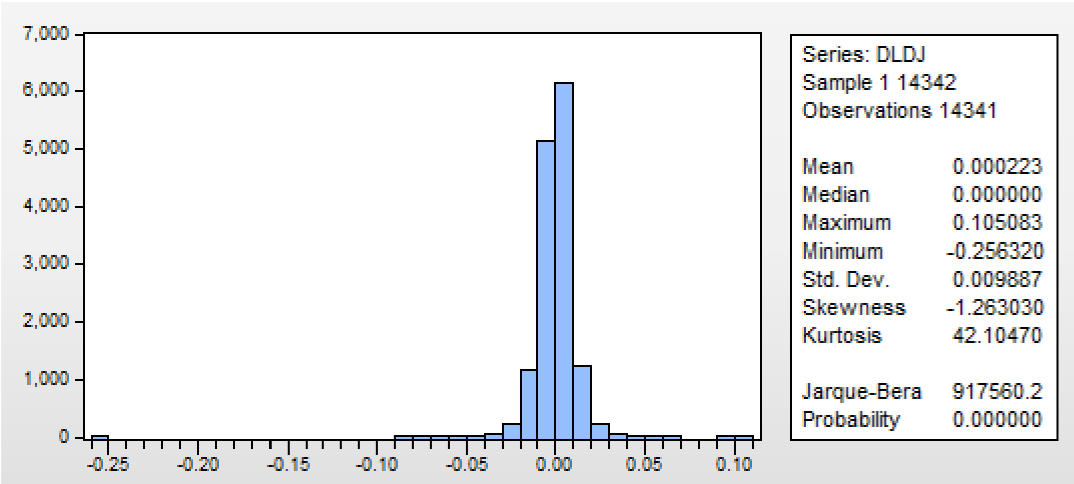


Table A.2.: S&P 500 (Daily Stock Returns) – descriptive statistics results (02/01/1957-22/12/2011)

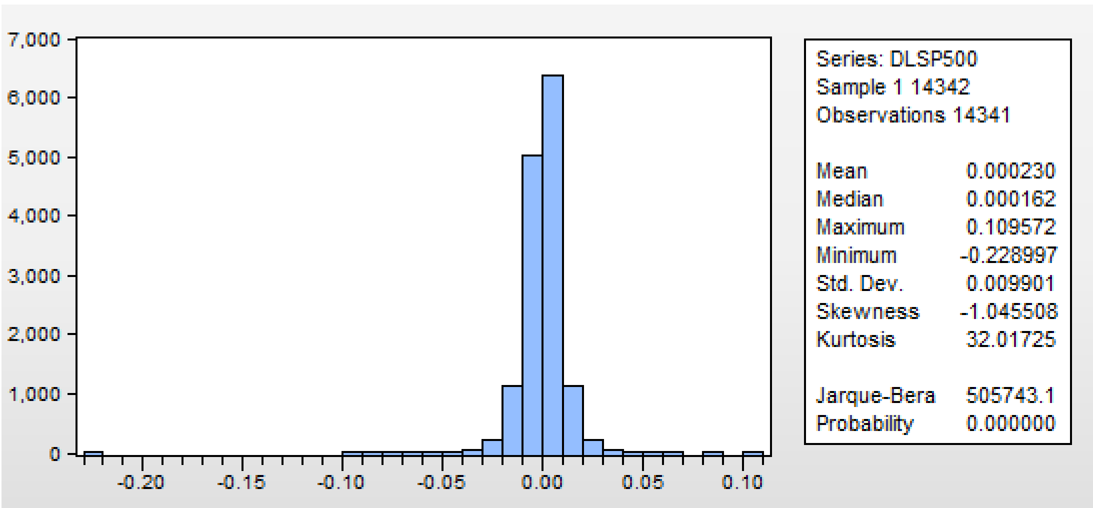


Table A.3.: 3-month Treasury Bill (Daily Returns) – descriptive statistics results (02/01/1957-22/12/2011)

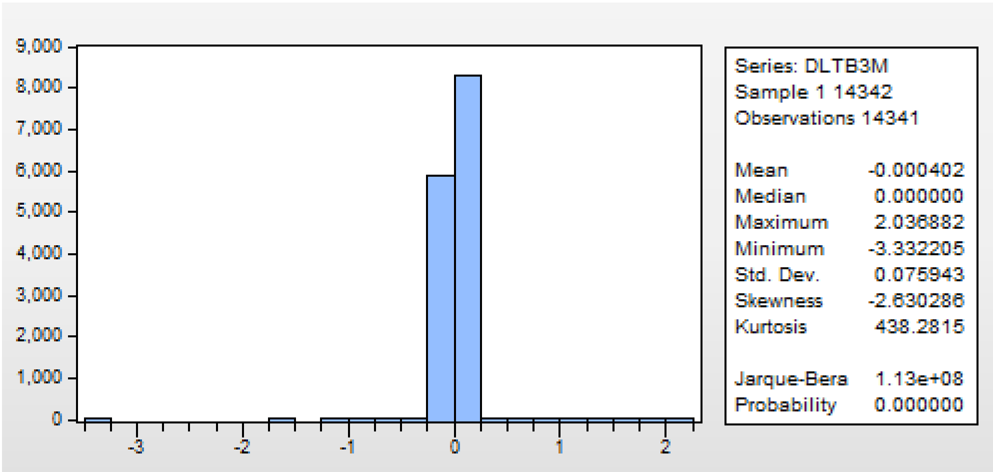


Table A.4.: Dow Jones (Excess Daily Stock Returns) – descriptive statistics results (02/01/1957-09/03/2000)

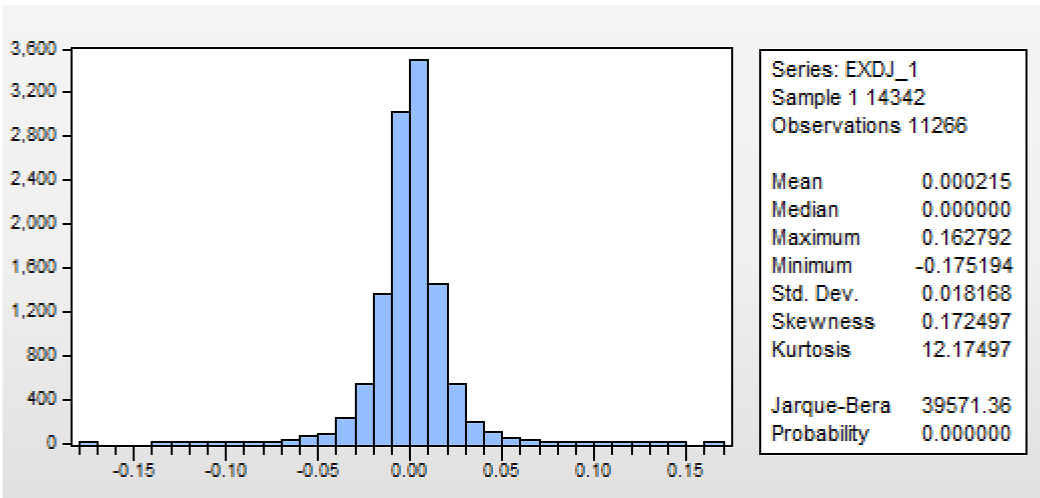


Table A.5.: S&P 500 (Excess Daily Stock Returns) – descriptive statistics results (02/01/1957-09/03/2000)

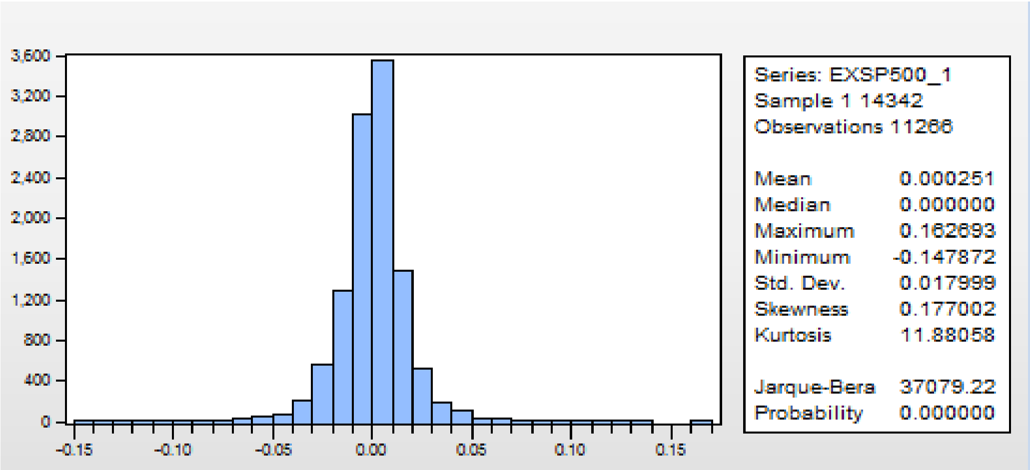


Table A.6.: Dow Jones (Excess Daily Stock Returns) – descriptive statistics results (10/03/2000-22/12/2011)

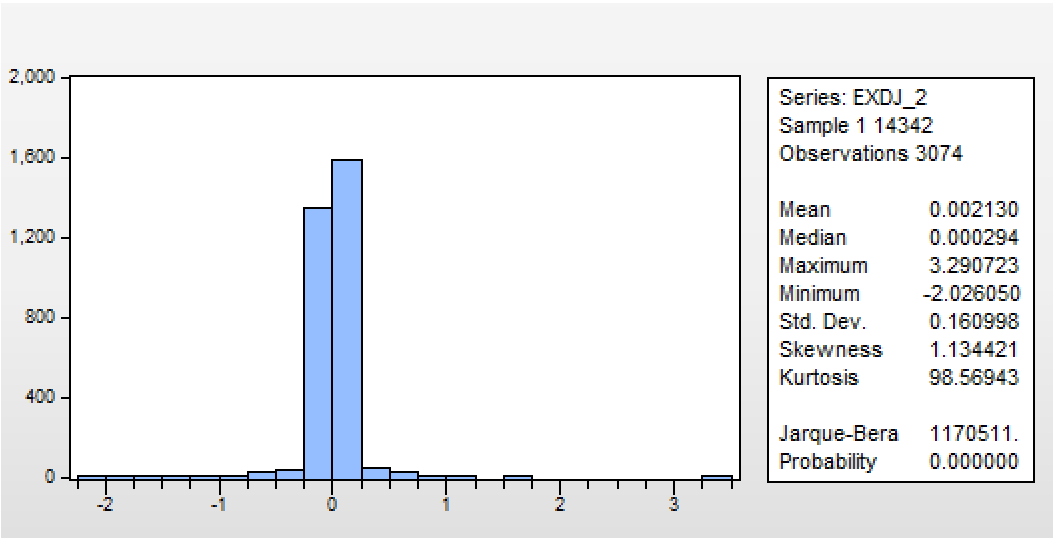


Table A.7.: S&P 500 (Excess Daily Stock Returns) – descriptive statistics results (10/03/2000-22/12/2011)

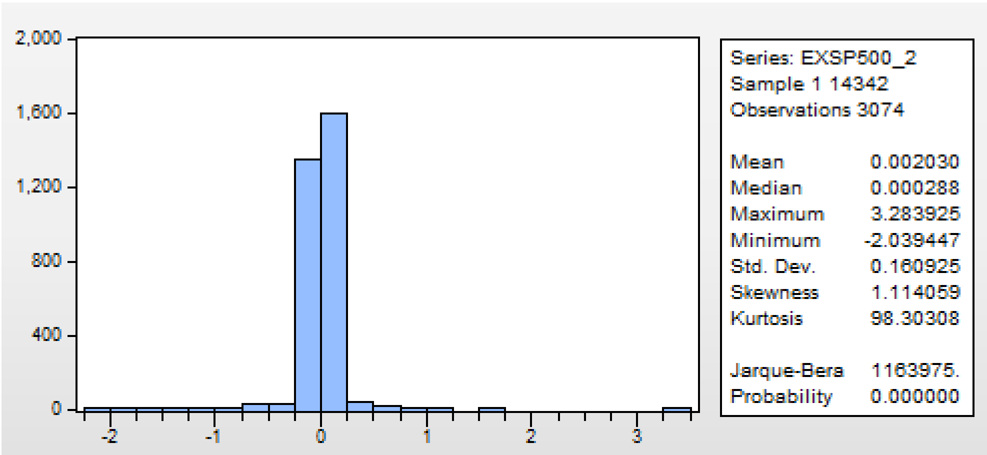


Figure A.1.: Dow Jones Excess Returns Correlogram (period 02/01/1957-22/12/2011)

Date: 01/17/12 Time: 10:18
Sample: 1 14342
Included observations: 14341

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.174	-0.174	436.09	0.000
*| |	*| |	2	-0.148	-0.184	752.15	0.000
| |	*| |	3	-0.009	-0.077	753.36	0.000
*| |	*| |	4	-0.090	-0.145	868.40	0.000
|* |	| |	5	0.131	0.073	1112.8	0.000
| |	| |	6	0.026	0.031	1122.3	0.000
*| |	| |	7	-0.083	-0.045	1222.1	0.000
*| |	*| |	8	-0.098	-0.127	1360.7	0.000
| |	| |	9	0.064	0.018	1418.7	0.000
| |	| |	10	0.009	-0.028	1419.9	0.000
| |	| |	11	0.015	-0.001	1423.0	0.000
| |	| |	12	0.045	0.047	1452.6	0.000
*| |	*| |	13	-0.118	-0.069	1653.6	0.000
| |	| |	14	0.019	-0.015	1659.0	0.000
|* |	| |	15	0.102	0.068	1808.4	0.000
| |	| |	16	-0.011	0.021	1810.2	0.000
| |	| |	17	0.002	0.017	1810.3	0.000
| |	| |	18	-0.039	-0.011	1832.7	0.000
| |	| |	19	-0.057	-0.043	1879.2	0.000
|* |	|* |	20	0.138	0.101	2154.2	0.000
| |	| |	21	-0.026	-0.020	2164.1	0.000
| |	| |	22	-0.034	0.007	2180.9	0.000
| |	| |	23	-0.037	-0.035	2200.6	0.000
*| |	*| |	24	-0.072	-0.077	2275.3	0.000
|* |	| |	25	0.123	0.068	2491.7	0.000
| |	| |	26	-0.006	-0.017	2492.2	0.000
| |	| |	27	-0.021	-0.002	2498.3	0.000
*| |	*| |	28	-0.087	-0.070	2608.0	0.000
| |	| |	29	0.039	0.020	2629.4	0.000
| |	| |	30	0.073	0.039	2707.0	0.000
| |	| |	31	0.033	0.048	2722.3	0.000

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 |    |         |    |     32  -0.060  -0.062  2774.7  0.000
 |    |         |    |     33  -0.063  -0.008  2832.4  0.000
 |    |         |    |     34   0.060   0.031  2884.9  0.000
 |    |         |    |     35   0.046   0.030  2915.2  0.000
 |    |         |    |     36  -0.032  -0.034  2929.6  0.000
 |    |         |    |     37  -0.003  -0.000  2929.7  0.000
*|    |         |    |     38  -0.072  -0.036  3003.6  0.000
 |    |         |    |     39   0.020   0.013  3009.6  0.000
 |    |         |    |     40   0.060   0.004  3061.2  0.000
 |    |         |    |     41  -0.020  -0.011  3066.9  0.000
 |    |         |    |     42  -0.010  -0.005  3068.2  0.000
 |    |         |    |     43  -0.038  -0.019  3088.8  0.000
 |    |         |    |     44  -0.006   0.005  3089.4  0.000
 |    |         |    |     45   0.032  -0.029  3104.4  0.000
 |    |         |    |     46   0.061   0.044  3158.2  0.000
 |    |         |    |     47   0.027   0.068  3169.1  0.000
*|    |         |    |     48  -0.117  -0.054  3366.9  0.000
 |    |         |    |     49   0.006  -0.017  3367.4  0.000
 |    |         |    |     50   0.039   0.001  3388.9  0.000
 |    |         |    |     51   0.006  -0.018  3389.4  0.000
 |*   |         |*   |     52   0.090   0.094  3505.0  0.000
*|    |        *|    |     53  -0.164  -0.087  3890.5  0.000
 |    |         |    |     54  -0.000  -0.013  3890.5  0.000
 |    |         |    |     55   0.064   0.005  3948.7  0.000
 |    |         |    |     56   0.001  -0.012  3948.7  0.000
 |    |         |    |     57  -0.010  -0.021  3950.0  0.000
 |    |         |    |     58  -0.024   0.012  3958.2  0.000
 |    |         |    |     59   0.011   0.016  3959.9  0.000
 |    |         |    |     60   0.002  -0.010  3960.0  0.000
 |*   |         |    |     61   0.078   0.043  4048.7  0.000
 |    |         |    |     62  -0.033  -0.002  4064.7  0.000
 |    |         |    |     63  -0.049   0.002  4099.5  0.000
 |    |         |    |     64   0.031  -0.011  4113.0  0.000
 |    |         |    |     65  -0.025  -0.003  4121.8  0.000
 |    |         |    |     66  -0.000  -0.045  4121.8  0.000
 |    |         |    |     67  -0.005  -0.041  4122.2  0.000
 |    |         |    |     68  -0.016   0.025  4125.7  0.000
 |    |         |    |     69   0.010   0.010  4127.1  0.000
 |    |         |    |     70   0.040   0.030  4150.0  0.000
 |    |         |    |     71  -0.025  -0.012  4158.8  0.000
 |    |         |    |     72   0.015  -0.006  4161.9  0.000
 |    |         |    |     73  -0.034  -0.010  4178.7  0.000
 |    |         |    |     74  -0.043  -0.046  4205.6  0.000
 |*   |         |    |     75   0.082   0.045  4302.0  0.000
 |    |         |    |     76  -0.032  -0.043  4316.5  0.000
 |    |         |    |     77   0.031   0.013  4330.6  0.000
 |    |         |    |     78  -0.052  -0.016  4369.1  0.000
 |    |         |    |     79  -0.011  -0.001  4371.0  0.000
 |    |         |    |     80   0.021  -0.011  4377.5  0.000
 |    |         |    |     81   0.009  -0.037  4378.6  0.000
 |    |         |    |     82  -0.019  -0.019  4384.0  0.000
 |    |         |    |     83  -0.046  -0.019  4414.2  0.000
 |    |         |    |     84   0.043   0.028  4441.3  0.000
 |    |         |    |     85   0.010   0.009  4442.8  0.000
 |    |         |    |     86  -0.001  -0.030  4442.8  0.000
 |    |         |    |     87  -0.003   0.003  4442.9  0.000
 |    |         |    |     88  -0.017   0.024  4447.3  0.000
 |    |         |    |     89   0.024   0.005  4455.8  0.000
 |    |         |    |     90   0.021   0.015  4462.1  0.000
 |    |         |    |     91   0.013   0.017  4464.7  0.000
 |    |         |    |     92   0.018   0.043  4469.5  0.000
 |    |         |    |     93  -0.048  -0.018  4503.1  0.000
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| |	| |	94	0.009	0.023	4504.4	0.000
| |	| |	95	0.051	0.039	4541.9	0.000
| |	| |	96	-0.026	-0.000	4552.0	0.000
| |	| |	97	-0.022	-0.023	4558.9	0.000
| |	| |	98	-0.030	-0.033	4571.6	0.000
| |	| |	99	0.007	0.004	4572.3	0.000
| |	| |	100	0.044	0.039	4600.8	0.000

Figure A.2.: S&P 500 Excess Returns Correlogram – (period 02/01/1957-22/12/2011)

Date: 01/17/12 Time: 10:18
Sample: 1 14342
Included observations: 14341

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.175	-0.175	440.13	0.000
*| |	*| |	2	-0.148	-0.185	755.15	0.000
| |	*| |	3	-0.010	-0.078	756.64	0.000
*| |	*| |	4	-0.089	-0.145	871.17	0.000
|* |	| |	5	0.131	0.072	1115.8	0.000
| |	| |	6	0.026	0.031	1125.4	0.000
*| |	| |	7	-0.084	-0.046	1226.7	0.000
*| |	*| |	8	-0.098	-0.127	1365.6	0.000
| |	| |	9	0.063	0.017	1423.2	0.000
| |	| |	10	0.010	-0.028	1424.5	0.000
| |	| |	11	0.014	-0.002	1427.5	0.000
| |	| |	12	0.045	0.046	1457.0	0.000
*| |	*| |	13	-0.118	-0.069	1657.9	0.000
| |	| |	14	0.019	-0.017	1662.9	0.000
|* |	| |	15	0.103	0.068	1814.8	0.000
| |	| |	16	-0.012	0.020	1817.0	0.000
| |	| |	17	0.002	0.016	1817.1	0.000
| |	| |	18	-0.039	-0.011	1839.5	0.000
| |	| |	19	-0.056	-0.043	1885.0	0.000
|* |	|* |	20	0.139	0.102	2163.4	0.000
| |	| |	21	-0.027	-0.019	2173.5	0.000
| |	| |	22	-0.035	0.006	2191.0	0.000
| |	| |	23	-0.037	-0.034	2210.4	0.000
*| |	*| |	24	-0.072	-0.077	2285.2	0.000
|* |	| |	25	0.123	0.068	2504.3	0.000
| |	| |	26	-0.007	-0.018	2505.0	0.000
| |	| |	27	-0.020	-0.001	2510.4	0.000
*| |	*| |	28	-0.089	-0.071	2625.0	0.000
| |	| |	29	0.039	0.019	2646.8	0.000
| |	| |	30	0.073	0.037	2724.0	0.000
| |	| |	31	0.033	0.048	2739.2	0.000
| |	| |	32	-0.061	-0.063	2792.5	0.000
| |	| |	33	-0.064	-0.009	2850.8	0.000
| |	| |	34	0.061	0.031	2904.4	0.000
| |	| |	35	0.046	0.030	2934.9	0.000
| |	| |	36	-0.032	-0.035	2950.1	0.000
| |	| |	37	-0.003	-0.000	2950.2	0.000
*| |	| |	38	-0.072	-0.036	3024.0	0.000
| |	| |	39	0.020	0.012	3029.8	0.000
| |	| |	40	0.061	0.005	3083.2	0.000
| |	| |	41	-0.021	-0.011	3089.3	0.000
| |	| |	42	-0.011	-0.007	3091.1	0.000

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  |   |          |   |     43  -0.037  -0.019  3111.4  0.000
  |   |          |   |     44  -0.007   0.005  3112.0  0.000
  |   |          |   |     45   0.033  -0.029  3127.8  0.000
  |   |          |   |     46   0.061   0.044  3181.8  0.000
  |   |          |   |     47   0.026   0.067  3191.4  0.000
 *|   |          |   |     48  -0.117  -0.053  3386.9  0.000
  |   |          |   |     49   0.007  -0.017  3387.5  0.000
  |   |          |   |     50   0.039   0.002  3410.0  0.000
  |   |          |   |     51   0.006  -0.018  3410.5  0.000
  |*  |          |*  |     52   0.089   0.094  3524.9  0.000
 *|   |         *|   |     53  -0.165  -0.087  3916.0  0.000
  |   |          |   |     54  -0.000  -0.014  3916.0  0.000
  |   |          |   |     55   0.064   0.006  3975.8  0.000
  |   |          |   |     56   0.001  -0.013  3975.8  0.000
  |   |          |   |     57  -0.010  -0.021  3977.3  0.000
  |   |          |   |     58  -0.024   0.012  3985.3  0.000
  |   |          |   |     59   0.011   0.017  3987.1  0.000
  |   |          |   |     60   0.003  -0.011  3987.2  0.000
  |*  |          |   |     61   0.078   0.044  4074.7  0.000
  |   |          |   |     62  -0.033  -0.001  4090.6  0.000
  |   |          |   |     63  -0.050   0.002  4126.2  0.000
  |   |          |   |     64   0.031  -0.011  4140.0  0.000
  |   |          |   |     65  -0.024  -0.003  4148.3  0.000
  |   |          |   |     66  -0.000  -0.044  4148.3  0.000
  |   |          |   |     67  -0.005  -0.041  4148.7  0.000
  |   |          |   |     68  -0.016   0.025  4152.4  0.000
  |   |          |   |     69   0.010   0.011  4153.9  0.000
  |   |          |   |     70   0.040   0.030  4176.8  0.000
  |   |          |   |     71  -0.025  -0.013  4185.8  0.000
  |   |          |   |     72   0.014  -0.007  4188.6  0.000
  |   |          |   |     73  -0.034  -0.011  4205.7  0.000
  |   |          |   |     74  -0.043  -0.046  4232.0  0.000
  |*  |          |   |     75   0.083   0.046  4330.8  0.000
  |   |          |   |     76  -0.032  -0.043  4345.8  0.000
  |   |          |   |     77   0.031   0.013  4359.7  0.000
  |   |          |   |     78  -0.051  -0.016  4397.9  0.000
  |   |          |   |     79  -0.011  -0.001  4399.7  0.000
  |   |          |   |     80   0.022  -0.011  4406.5  0.000
  |   |          |   |     81   0.009  -0.037  4407.8  0.000
  |   |          |   |     82  -0.021  -0.020  4414.0  0.000
  |   |          |   |     83  -0.046  -0.019  4444.4  0.000
  |   |          |   |     84   0.044   0.029  4472.8  0.000
  |   |          |   |     85   0.010   0.009  4474.4  0.000
  |   |          |   |     86  -0.001  -0.030  4474.4  0.000
  |   |          |   |     87  -0.003   0.003  4474.5  0.000
  |   |          |   |     88  -0.018   0.025  4479.0  0.000
  |   |          |   |     89   0.024   0.004  4487.1  0.000
  |   |          |   |     90   0.021   0.015  4493.7  0.000
  |   |          |   |     91   0.013   0.018  4496.1  0.000
  |   |          |   |     92   0.018   0.043  4500.9  0.000
  |   |          |   |     93  -0.048  -0.017  4534.7  0.000
  |   |          |   |     94   0.009   0.024  4536.0  0.000
  |   |          |   |     95   0.052   0.040  4575.6  0.000
  |   |          |   |     96  -0.026   0.001  4585.5  0.000
  |   |          |   |     97  -0.022  -0.023  4592.6  0.000
  |   |          |   |     98  -0.029  -0.032  4605.2  0.000
  |   |          |   |     99   0.007   0.005  4605.8  0.000
  |   |          |   |    100   0.045   0.039  4634.7  0.000
```

Figure A.3.: Dow Jones Excess Returns Correlogram (period 02/01/1957-09/03/2000)

Date: 01/17/12 Time: 10:18
Sample: 1 14342
Included observations: 11266

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
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<tr><td>| |</td><td>| |</td><td>30</td><td>0.043</td><td>0.026</td><td>600.87</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>31</td><td>-0.024</td><td>-0.023</td><td>607.24</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>32</td><td>-0.015</td><td>-0.009</td><td>609.82</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>33</td><td>-0.017</td><td>-0.013</td><td>613.15</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>34</td><td>-0.018</td><td>-0.012</td><td>616.87</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>35</td><td>0.039</td><td>0.023</td><td>633.63</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>36</td><td>-0.016</td><td>-0.013</td><td>636.68</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>37</td><td>-0.001</td><td>0.005</td><td>636.68</td><td>0.000</td></tr>
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<tr><td>| |</td><td>| |</td><td>39</td><td>0.009</td><td>0.014</td><td>637.92</td><td>0.000</td></tr>
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<tr><td>| |</td><td>| |</td><td>46</td><td>-0.035</td><td>-0.030</td><td>735.61</td><td>0.000</td></tr>
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<tr><td>| |</td><td>| |</td><td>50</td><td>0.031</td><td>0.015</td><td>751.53</td><td>0.000</td></tr>
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</table>

54	0.001	0.013	755.69	0.000
55	0.033	0.011	768.07	0.000
56	-0.040	-0.036	786.42	0.000
57	-0.030	-0.021	796.69	0.000
58	-0.017	-0.003	799.89	0.000
59	-0.020	-0.016	804.48	0.000
60	0.025	0.010	811.51	0.000
61	0.004	0.015	811.67	0.000
62	0.009	0.003	812.60	0.000
63	0.003	0.003	812.73	0.000
64	-0.001	-0.001	812.74	0.000
65	0.039	0.019	830.28	0.000
66	0.005	0.008	830.52	0.000
67	-0.005	-0.010	830.86	0.000
68	-0.015	-0.008	833.37	0.000
69	-0.014	-0.005	835.57	0.000
70	0.035	0.020	849.43	0.000
71	-0.021	-0.019	854.27	0.000
72	-0.010	-0.004	855.44	0.000
73	-0.013	-0.004	857.40	0.000
74	-0.013	-0.005	859.22	0.000
75	0.037	0.022	874.93	0.000
76	-0.026	-0.024	882.49	0.000
77	0.004	0.012	882.65	0.000
78	-0.015	-0.012	885.21	0.000
79	0.007	0.015	885.77	0.000
80	0.039	0.016	902.88	0.000
81	-0.007	-0.002	903.40	0.000
82	0.004	0.002	903.58	0.000
83	-0.020	-0.017	908.18	0.000
84	-0.010	-0.002	909.26	0.000
85	0.037	0.019	924.98	0.000
86	-0.000	0.004	924.98	0.000
87	-0.019	-0.023	928.88	0.000
88	-0.005	0.010	929.12	0.000
89	-0.003	-0.002	929.24	0.000
90	0.055	0.034	963.80	0.000
91	-0.001	-0.005	963.81	0.000
92	-0.036	-0.038	978.43	0.000
93	-0.021	-0.002	983.38	0.000
94	-0.009	-0.002	984.34	0.000
95	0.029	0.008	993.81	0.000
96	-0.016	-0.006	996.63	0.000
97	-0.010	0.002	997.71	0.000
98	-0.013	-0.004	999.52	0.000
99	0.005	0.012	999.81	0.000
100	0.026	0.002	1007.2	0.000

Figure A.4.: S&P 500 Excess Returns Correlogram (period 02/01/1957-09/03/2000)

Date: 01/17/12 Time: 10:18
Sample: 1 14342
Included observations: 11266

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.153	0.153	264.74	0.000
| |	| |	2	0.023	-0.000	270.86	0.000
| |	| |	3	-0.003	-0.007	270.99	0.000
| |	| |	4	0.002	0.004	271.04	0.000
|* |	|* |	5	0.077	0.078	337.20	0.000
| |	| |	6	-0.023	-0.048	343.39	0.000
| |	| |	7	-0.015	-0.006	345.99	0.000
| |	| |	8	-0.013	-0.008	347.95	0.000
| |	| |	9	-0.010	-0.006	349.02	0.000
|* |	|* |	10	0.083	0.081	426.52	0.000
| |	| |	11	0.003	-0.017	426.62	0.000
| |	| |	12	0.002	0.002	426.66	0.000
| |	| |	13	-0.011	-0.010	428.04	0.000
| |	| |	14	-0.015	-0.011	430.65	0.000
| |	| |	15	0.066	0.059	480.11	0.000
| |	| |	16	-0.001	-0.014	480.11	0.000
| |	| |	17	-0.012	-0.011	481.67	0.000
| |	| |	18	-0.007	0.000	482.26	0.000
| |	| |	19	0.004	0.009	482.40	0.000
| |	| |	20	0.073	0.056	543.19	0.000
| |	| |	21	-0.014	-0.030	545.35	0.000
| |	| |	22	0.004	0.011	545.55	0.000
| |	| |	23	0.003	0.004	545.62	0.000
| |	| |	24	0.020	0.022	549.98	0.000
| |	| |	25	0.071	0.047	607.04	0.000
| |	| |	26	-0.021	-0.033	611.98	0.000
| |	| |	27	-0.006	0.001	612.42	0.000
| |	| |	28	0.005	0.010	612.66	0.000
| |	| |	29	-0.008	-0.010	613.40	0.000
| |	| |	30	0.044	0.026	635.18	0.000
| |	| |	31	-0.027	-0.027	643.48	0.000
| |	| |	32	-0.017	-0.010	646.76	0.000
| |	| |	33	-0.018	-0.011	650.35	0.000
| |	| |	34	-0.020	-0.014	654.65	0.000
| |	| |	35	0.042	0.026	674.58	0.000
| |	| |	36	-0.017	-0.015	678.03	0.000
| |	| |	37	-0.008	-0.002	678.68	0.000
| |	| |	38	-0.009	-0.005	679.50	0.000
| |	| |	39	0.009	0.015	680.50	0.000
|* |	| |	40	0.077	0.053	747.20	0.000
| |	| |	41	0.003	-0.004	747.33	0.000
| |	| |	42	0.014	0.015	749.55	0.000
| |	| |	43	-0.003	-0.005	749.64	0.000
| |	| |	44	-0.001	0.000	749.65	0.000
| |	| |	45	0.040	0.017	767.68	0.000
| |	| |	46	-0.032	-0.028	779.16	0.000
| |	| |	47	-0.000	0.008	779.16	0.000
| |	| |	48	-0.004	-0.001	779.34	0.000
| |	| |	49	-0.018	-0.016	782.94	0.000
| |	| |	50	0.034	0.016	795.82	0.000
| |	| |	51	-0.002	0.006	795.86	0.000
| |	| |	52	0.001	-0.005	795.87	0.000
| |	| |	53	-0.022	-0.019	801.50	0.000

54	0.001	0.014	801.52	0.000
55	0.031	0.007	812.71	0.000
56	-0.043	-0.037	833.64	0.000
57	-0.031	-0.020	844.33	0.000
58	-0.019	-0.004	848.35	0.000
59	-0.020	-0.016	852.99	0.000
60	0.030	0.014	862.87	0.000
61	0.004	0.014	863.01	0.000
62	0.009	0.005	864.01	0.000
63	0.002	0.002	864.04	0.000
64	-0.001	-0.002	864.06	0.000
65	0.040	0.019	882.15	0.000
66	-0.001	0.003	882.16	0.000
67	-0.005	-0.007	882.40	0.000
68	-0.015	-0.008	885.11	0.000
69	-0.014	-0.006	887.35	0.000
70	0.035	0.019	901.39	0.000
71	-0.024	-0.020	907.71	0.000
72	-0.011	-0.004	909.05	0.000
73	-0.013	-0.004	911.04	0.000
74	-0.010	-0.003	912.27	0.000
75	0.037	0.020	927.80	0.000
76	-0.024	-0.020	934.29	0.000
77	0.006	0.013	934.66	0.000
78	-0.014	-0.011	936.93	0.000
79	0.005	0.013	937.27	0.000
80	0.041	0.018	956.51	0.000
81	-0.007	-0.001	957.03	0.000
82	0.005	0.003	957.35	0.000
83	-0.023	-0.019	963.20	0.000
84	-0.008	0.000	964.00	0.000
85	0.039	0.019	981.44	0.000
86	-0.002	0.002	981.51	0.000
87	-0.017	-0.021	984.64	0.000
88	-0.006	0.009	984.99	0.000
89	0.000	0.000	984.99	0.000
90	0.056	0.033	1020.6	0.000
91	0.001	-0.001	1020.6	0.000
92	-0.035	-0.038	1034.2	0.000
93	-0.022	-0.003	1039.8	0.000
94	-0.009	-0.002	1040.8	0.000
95	0.031	0.010	1051.6	0.000
96	-0.013	-0.003	1053.4	0.000
97	-0.009	0.001	1054.2	0.000
98	-0.007	0.004	1054.8	0.000
99	0.004	0.007	1054.9	0.000
100	0.027	0.002	1063.0	0.000

Figure A.5.: Dow Jones Excess Returns Correlogram (period 10/03/2000-22/12/2011)

Date: 01/15/12 Time: 19:00
Sample: 1 14342
Included observations: 3074

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
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<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.157</td><td>-0.200</td><td>186.03</td><td>0.000</td></tr>
<tr><td>| |</td><td>*| |</td><td>3</td><td>-0.010</td><td>-0.090</td><td>186.31</td><td>0.000</td></tr>
<tr><td>*| |</td><td>*| |</td><td>4</td><td>-0.094</td><td>-0.161</td><td>213.45</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>5</td><td>0.133</td><td>0.062</td><td>267.93</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.028</td><td>0.029</td><td>270.34</td><td>0.000</td></tr>
<tr><td>*| |</td><td>| |</td><td>7</td><td>-0.087</td><td>-0.048</td><td>293.50</td><td>0.000</td></tr>
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<tr><td>| |</td><td>| |</td><td>9</td><td>0.067</td><td>0.011</td><td>339.69</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>0.006</td><td>-0.038</td><td>339.79</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>11</td><td>0.015</td><td>-0.009</td><td>340.49</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>12</td><td>0.047</td><td>0.043</td><td>347.40</td><td>0.000</td></tr>
<tr><td>*| |</td><td>*| |</td><td>13</td><td>-0.124</td><td>-0.074</td><td>394.53</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>14</td><td>0.021</td><td>-0.021</td><td>395.87</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>15</td><td>0.104</td><td>0.065</td><td>429.16</td><td>0.000</td></tr>
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Figure A.6.: S&P 500 Excess Returns Correlogram (period 10/03/2000-22/12/2011)

Date: 01/15/12 Time: 18:58
Sample: 1 14342
Included observations: 3074

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<tr><td>| |</td><td>| |</td><td>46</td><td>0.065</td><td>0.043</td><td>744.85</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>47</td><td>0.027</td><td>0.071</td><td>747.14</td><td>0.000</td></tr>
<tr><td>*| |</td><td>| |</td><td>48</td><td>-0.122</td><td>-0.054</td><td>793.51</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>49</td><td>0.008</td><td>-0.019</td><td>793.69</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>50</td><td>0.040</td><td>-0.001</td><td>798.61</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>51</td><td>0.006</td><td>-0.022</td><td>798.73</td><td>0.000</td></tr>
<tr><td>|* |</td><td>|* |</td><td>52</td><td>0.093</td><td>0.097</td><td>825.90</td><td>0.000</td></tr>
<tr><td>*| |</td><td>*| |</td><td>53</td><td>-0.171</td><td>-0.089</td><td>917.92</td><td>0.000</td></tr>
</table>

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|     |      |  |     54  -0.000  -0.017  917.92  0.000
|     |      |  |     55   0.066   0.003  931.47  0.000
|     |      |  |     56   0.002  -0.014  931.49  0.000
|     |      |  |     57  -0.009  -0.021  931.76  0.000
|     |      |  |     58  -0.024   0.012  933.55  0.000
|     |      |  |     59   0.012   0.020  934.03  0.000
|     |      |  |     60   0.001  -0.010  934.04  0.000
|*    |      |  |     61   0.081   0.045  954.76  0.000
|     |      |  |     62  -0.035   0.000  958.67  0.000
|     |      |  |     63  -0.052   0.002  967.21  0.000
|     |      |  |     64   0.032  -0.013  970.49  0.000
|     |      |  |     65  -0.027  -0.005  972.80  0.000
|     |      |  |     66  -0.000  -0.050  972.80  0.000
|     |      |  |     67  -0.005  -0.048  972.88  0.000
|     |      |  |     68  -0.016   0.021  973.72  0.000
|     |      |  |     69   0.011   0.010  974.12  0.000
|     |      |  |     70   0.040   0.030  979.16  0.000
|     |      |  |     71  -0.025  -0.011  981.14  0.000
|     |      |  |     72   0.015  -0.008  981.84  0.000
|     |      |  |     73  -0.036  -0.013  985.84  0.000
|     |      |  |     74  -0.044  -0.051  992.04  0.000
|*    |      |  |     75   0.085   0.044  1014.7  0.000
|     |      |  |     76  -0.033  -0.047  1018.1  0.000
|     |      |  |     77   0.032   0.009  1021.3  0.000
|     |      |  |     78  -0.053  -0.018  1030.3  0.000
|     |      |  |     79  -0.012  -0.003  1030.8  0.000
|     |      |  |     80   0.021  -0.015  1032.1  0.000
|     |      |  |     81   0.010  -0.043  1032.4  0.000
|     |      |  |     82  -0.022  -0.026  1034.0  0.000
|     |      |  |     83  -0.047  -0.025  1041.0  0.000
|     |      |  |     84   0.047   0.027  1047.8  0.000
|     |      |  |     85   0.009   0.007  1048.1  0.000
|     |      |  |     86  -0.001  -0.034  1048.1  0.000
|     |      |  |     87  -0.002   0.000  1048.1  0.000
|     |      |  |     88  -0.018   0.023  1049.2  0.000
|     |      |  |     89   0.025   0.002  1051.1  0.000
|     |      |  |     90   0.020   0.011  1052.3  0.000
|     |      |  |     91   0.013   0.016  1052.9  0.000
|     |      |  |     92   0.021   0.048  1054.2  0.000
|     |      |  |     93  -0.050  -0.016  1062.1  0.000
|     |      |  |     94   0.010   0.027  1062.4  0.000
|     |      |  |     95   0.053   0.045  1071.4  0.000
|     |      |  |     96  -0.027   0.005  1073.7  0.000
|     |      |  |     97  -0.023  -0.020  1075.4  0.000
|     |      |  |     98  -0.031  -0.036  1078.3  0.000
|     |      |  |     99   0.007   0.003  1078.5  0.000
|     |      |  |    100   0.045   0.041  1085.0  0.000
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