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Behavioral finance explaining excessive volatility of returns on financial instruments

Author: **Šárka Křížková**

Supervisor: **PhDr. Jiří Kameníček, CSc.**

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Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor, that the references include all resources and literature I have used and that this thesis has not been used to obtain any other university diploma.

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Prague, May 12, 2016

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Abstract

The main focus of this thesis is to comprehensively describe the area of research called Behavioral finance and to point out a theory which has existed over 30 years but it is still not further developed: the Prospect theory. It has an application in many areas including finance - the major of this work. The thesis analyses the volatility of returns on futures contracts on cotton, crude oil and S&P 500 index using ARCH type models. The analysis confirms an asymmetric leverage effect of returns on volatility of all of the three contracts which corroborates a loss aversion in the decision making of investors, one of the main features of Prospect theory. On the other hand a measure of investor sentiment defined using open interest information incorporated in the model to directly capture investors reactions proved to be a weak tool.

JEL Classificiation	D03, D81, G02, G12, G13, G14, C52
Keywords	behavioral finance, prospect theory, futures market, loss aversion, ARCH models

Author's email	saarka.krizkova@gmail.com
Supervisor's email	jiri.kamenicek@fsv.cuni.cz

Abstrakt

Hlavním cílem této práce je komplexně popsat oblast výzkumu zvanou Behaviorální finance a vyzdvihnout teorii, která přesto, že existuje již přes 30 let, nebyla stále podrobena dalšímu zkoumání, které by ji posunulo dál: Teorii vyhlídek. Tato teorie má uplatnění v mnoha oblastech včetně financí - hlavního tématu této práce. Za použití ARCH typu modelů práce analyzuje volatilitu výnosů z futurových kontraktů na bavlnu, ropu a S&P 500 index. Analýza potvrzuje asymetrický efekt výnosů na volatilitu všech tří kontraktů. To potvrzuje averzi investorů ke ztrátám při jejich rozhodování, jeden z hlavních atributů Teorie vyhlídek. Na druhou stranu slabým nástrojem se v analýze ukázal být člen, který měl měřit sentiment investorů přímějším způsobem definovaným pomocí informace o množství otevřených kontraktů.

JEL klasifikace	D03, D81, G02, G12, G13, G14, C52
Klíčová slova	behaviorální finance, teorie vyhlídek, trh futurových kontraktů, averze ke ztrátě, ARCH modely

Email autora	saarka.krizkova@gmail.com
Email vedoucího práce	jiri.kamenicek@fsv.cuni.cz

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Acronyms

ACF Autocorrelation function

AIC Akaike information criterion

ARCH Autoregressive conditional heteroskedasticity

ARMA Autoregressive moving average

CPT Cumulative prospect theory

EARCH Exponential autoregressive conditional heteroskedasticity

EUT Expected utility theory

EMH Efficient market hypothesis

GARCH Generalized autoregressive conditional heteroskedasticity

LL Log Likelihood

LM Lagrange multiplier

PACF Partial autocorrelation function

PT Prospect theory

QLR Quandt Likelihood Ratio

SI Sentiment index

TARCH Threshold autoregressive conditional heteroskedasticity

Chapter 1

Introduction

Behavioral finance is a young and slowly developing major which emerged as a reaction on incapability of a normative economic theory to model the real world market behavior. It incorporates psychology and the aspect of non rationality of individuals in the explanation of the market behavior. Since I have been always interested in psychology and the decision making of different people a topic about behavioral economics was a clear choice. The original intention was to review the Prospect theory - a choice theory developed by Kahneman and Tversky in 1979 - only as it is because its well structured fundamentals and principals earned my attention. As I was studying the topic and its application in economics I have decided to narrow the matter to finance and try to perform a similar analysis of futures returns as Serrão (2015) undertook however using different contracts in various fields and explain the abnormalities discovered within a reasoning of behavioral finance.

The objective of this thesis is first to summarize the known facts about behavioral finance - its roots, complexity, theories and application - and thus provide a theoretical basis for the further research which analyses the volatility of futures returns. The goal of the analysis is to search for the stylized facts about volatility (generally known mainly from an investigation of the stock returns) in futures contracts on cotton, crude oil and S&P 500 index. A main focus is put on confirming the presence of a negative leverage effect in the data which is consequently a proof of a loss aversion of investors since their behavior influence the final price (and therefore the returns as well) of the instrument. The loss aversion in the provided data is mostly present and very strongly pronounced. There is also an attempt to incorporate a direct measure of an investor sentiment defined using open interest information. Nevertheless, it is not concluded to be a good measure of the assumed relationship in all of the three futures contracts examined.

The thesis is structured as follows: Chapter 2 discusses the general problem of an excessive volatility of returns in the contrast of Efficient Market Hypothesis and its observed distortions at the market. Chapter 3 describes the theoretical concepts of Efficient market hypothesis and Behavioral finance. A detailed description of the Prospect theory is given in Chapter 4. Chapter 5 describes how the futures markets work and in Chapter 6 an analysis of the volatility of the three futures contracts is performed.

Chapter 2

Stylized facts about volatility

Volatility is an important determinant at the financial market. It measures the degree of variation around the mean or average return of a security. Fluctuation of volatility of returns gives the meaning to investor's trading at the financial market. Yet according to the efficient market hypothesis, the financial market is efficient and it is impossible to "beat the market"[1] as stock prices cannot deviate from their fair values. Today there is no doubt that this theory does not hold in real market conditions. The missing piece is however a new and integral theory which would be consistent with actual behavior of stock prices. There are certain statistical regularities which capture the peculiarities of volatility called stylized facts. They have nevertheless a lack of a good economic reasoning. Dudokovic (2013) states that these facts are:

Volatility clustering and long memory in absolute values of returns. A time series of absolute values of returns is highly autocorrelated even for very far lags which indicates a long memory of the series. Volatility is not constant and it tends to cluster meaning the low volatility is likely to be followed by a low volatility period and vice versa.

Fat tail phenomena. The number of extremely high returns is much bigger than anticipated under the normal distribution, which is expected by the modern finance

[1] Bibliography [21]

theory. Moreover the density of the distribution is more peaked than the one of the normal distribution.

The leverage effect. Volatility and returns are negatively correlated. The relationship is asymmetric as negative returns (i.e. bad news)[2] bring larger increases in volatility than the decline in volatility that accompanies positive returns (good news).

The challenge for this work is to confirm the stated stylized facts using a suitable econometric model and to show that investors behavior has an influence on the volatility of returns at the futures market.

[2]Bad news for investors are considered to be linked with negative returns.

Chapter 3

Main investment theories and their theoretical foundations

3.1 Efficient market hypothesis

Efficient market hypothesis (EMH) - in its "strong form" - argues that the capital market is fully efficient, which means that it reflects all the relevant information (known to any market participant) to security prices that consequently mirror the correct asset values.[1] Hence, no one is able to earn any extraordinary risk-adjusted profits. Therefore, - as stated in Serrão (2015) - excessive volatility at the financial markets is not predicted to be feasible.

The two main theoretical assumptions for EMH are the **expected utility theory** (EUT) and the **rational expectations paradigm**. The former refers to a theory of choice under uncertainty, a normative model of rational choice. The theory states that if preferences satisfy axioms of completeness, transitivity, continuity and independence, they can be represented by Von Neumann-Morgenstern utility function.[2] Kahneman and Tversky (1979) characterized the three cornerstones of EUT - describing the expected utility function - as following:

[1] Fama (1970); Malkiel (2003)

[2] Barberis and Thaler (2003)

1. Expectation.

$$U(x_1, p_1; ....; x_n, p_n) = p_1 u(x_1) + ... + p_n u(x_n) \tag{3.1}$$

   The utility U of a prospect which yields outcome x_i with probability p_i - where $p_1 + ... + p_n = 1$ - equals to the expected utility of its outcomes.

2. Asset Integration.

   A prospect $(x_1, p_1; ....; x_n, p_n)$ is agreeable at the asset position w if:

$$U(w + x_1, p_1; ....; w + x_n, p_n) > u(w) \tag{3.2}$$

   A prospect is agreeable if the utility of adding the prospect to one's asset position exceeds the utility of that position itself.

3. Risk Aversion. u is concave: $u'' < 0$

   Individuals are risk averse if their utility function is concave meaning that they prefer a certain prospect x to any risky prospect with expected value x.

The **rational expectations paradigm** assumes investors to behave according to the EUT. Second, investors form their new belief - as new information becomes available - correctly according to the Bayes' rule[3] . Agents are all identical.

EMH along with **Modern portfolio theory** and **Capital asset pricing model** represent the normative wing of understanding the financial markets. The other wing incorporates psychology in its explanation of market behavior: thus called Behavioral finance.

3.2 Behavioral finance

A new approach in financial market theory has emerged in response to significant deviations of real world conditions and the EMH. Behavioral finance assumes that individuals are not always rational when deciding about their investments and that these individuals have an important effect on the development of asset prices.

[3]Barberis and Thaler (2003). The rule is defined in the subsection 3.2.2.

This work follows Barberis and Thaler's (2003) approach to present behavioral finance. In the traditional point of view it is believed that even though there are irrational traders (often called "**noise traders**") who can bias the actual price of assets from its fundamental value by their incorrect presumptions, rational agents will always quickly reverse their influence on those prices. The process of returning the price back to its fundamental value is called an "arbitrage" (hence rational agents are called "**arbitrageurs**"). The mechanism should work as follows[4]: arbitrageurs can recognize that the asset is underpriced and therefore they will purchase the security at the undervalued price and simultaneously short sell a "substitute" security of a company in the same field with comparable cash flows to hedge themselves against the risk of a drop in values of the original instrument.

Behavioral finance argues that those strategies often do not pay off. The methods for fixing the mispricing can be very risky and costly (fundamental risk, noise trader risk, implementation costs) hence it is not consequently rational to invest in those opportunities and thus the mispricing prevails much longer than expected by the traditional paradigm. Those risks and costs are generally called "**limits to arbitrage**" and they form one of the two cornerstones of behavioral finance. To understand how exactly people violate the EUT, **psychology** is employed and it mainly examines the way how people create their "*beliefs*" and how their *preferences* look like.

3.2.1 Limits to arbitrage

Undeniable risks which an investor faces are:

Fundamental risk. Further bad news about the fundamental value can worsen the price causing losses on initial investments. Even though the arbitrageurs hedged themselves with a substitute security, they still face the risk that this security is mispriced as well or that not only the company, but the whole industry will suffer from adverse news.

[4] In the examples in this section it is assumed that the fundamental value of a share is **pushed down** by pessimistic noise traders.

Noise trader risk. Arbitrageurs face the risk that noise traders who caused the mispricing will become even more pessimistic and thus affect the price to decrease even more. The noise trader risk is often a reason why arbitrageurs "liquidate their positions early". They are - that is to say - often educated portfolio managers who manage other people's money. These investors evaluate the managers according to their short run performance, i.e. short run returns. They are not able to look through the managers' strategies and thus - when they see that the returns are negative in the short run - they can "withdraw their funds" to protect themselves. Thus the managers are forced to liquidate their positions too soon.

Concerns that the previously stated could happen cause that the rational traders are generally also too conservative to try to exploit mispricing opportunities induced by noise traders. It is worth to mention that educated portfolio managers can sometimes also become noise traders and contribute to distortion of the security price as they can start to act like players since the money invested in the fund are not theirs and thus the risk aversion in the domain of gains can turn into risk seeking.

Arbitrageurs also face costs.

Implementation costs. Exploiting a mispricing brings various costs. In addition to transaction costs (commissions, bid-ask spreads, price impact) there are often very high costs of short selling which include not only the fees for opening a short position, but also legal obstacles or generally anything which causes the long position to be more appealing than the short one. Implementation costs also include the costs of "finding and learning about the mispricing".

3.2.2 Psychology

For deeper understanding on how exactly the mispricing occurs the behavioral economists derive their theories from an experimental field of a cognitive psychology. They explore people's preferences and a way how they form their beliefs.

Beliefs

Ritter (2003) and Barberis and Thaler (2003) summarize the characteristics of beliefs in following patterns:

- **Heuristics**. Heuristics are "mental shortcuts"[5] that are used to make the decision-making easier and faster. They are also known as "rules of thumb" or simply the "common sense". These beliefs can often lead to distortions in the process of composing an investor's portfolio as many important factors can be omitted from the decision-making. An example of this kind of behaviour is the *1/N rule* when people distribute their investments equally to each fund.

- **Overconfidence.** People are overconfident about their competence to evaluate a situation. For example, they tend to assign extreme values to the probabilities of events to occur: events which they consider almost certain actually occur around 80% of the time and events that are considered impossible occur 20% of the time[6]. People often invest in what is familiar for them. Therefore they invest too much in stocks of local companies or the companies where they work even though there is no rational reason for that.

- **Optimism and wishful thinking.** Many people are way too much optimistic about their abilities. They consider themselves to be over average in their skills. They tend to anticipate that they can finish their tasks sooner than they actually can in reality.

- **Mental accounting.** Mental accounting is present when people separately evaluate decisions which should be - by nature - evaluated together. The typical example is eating in a restaurant versus at home. People usually do not cook expensive meals at home whereas they do not mind to order fancy meals in restaurants. They evaluate both in separate categories even though it is actually only one category of food.

[5]Heuristic - Wikipedia (2016)

[6]Barberis and Thaler (2003)

- **Framing.** People evaluate prospects in accordance with the way how they are introduced to them. If there is one prospect which is presented in two different ways: in terms of losses and in terms of gains and people are asked to choose one of them, they tend to choose the one which is presented in terms of gains.[7]

- **Representativeness.** "When people try to determine the probability that a data set A was generated by a model B, or that an object A belongs to a class B, they often use the representativeness heuristic."[8] This means that if A is "highly representative" of B, the probability that A comes from B is evaluated to be high and the other way round.[9] Representativeness can be the source of distortions. It can generate "*base rate neglect*". According to the Bayes' law it holds that:

$$P(datasetA|modelB) = \frac{P(modelB|datasetA)P(datasetA)}{P(modelB)} \tag{3.3}$$

  People tend to put too much weight on the first term in the numerator and too little weight on the second term (the base rate) which indicates representativeness. Another bias known as "*sample size neglect*" or *law of small numbers* causes that people often do not account for the size of the sample when evaluating the probabilities. Ritter (2003) gives an example of equity returns. When these returns are very high for a longer period (several years), people begin to consider it as generally highly profitable investment opportunity.

- **Conservatism.** There are as well cases that lead to over weighting the base rates. These cases often arise when the sample evidence is not highly representative of the model and thus conservatism comes into play and people tend to over rely on the prior information.

- **Belief perseverance.** When a certain belief has been formed, people usually adhere to it tightly and for a long time.

[7]Tversky and Kahneman (1992)

[8]Barberis and Thaler (2003), page 1064

[9]Tversky and Kahneman (1974)

- **Anchoring.** Often people create estimates based on their initial uneducated guess (or a value suggested externally when the authority explains the problem) by deviating from that value to yield the final result.[10] This adjustment is often not enough.

- **Availability biases.** Estimating the probability of an event is based on people's memories which are however substantially distorted as some memories are more powerful than others and people tend to put more weight on those ones when evaluating the probabilities. More recent events have also a higher weight.

Preferences - Prospect theory

As far as the knowledge of the author goes, PT is the only descriptive model in behavioral economics which explains the irrational behavior of economic agents with consistent and solid assumptions which effectively match the experimental evidence.

Kahneman and Tversky (1979) have presented a set of pair problems in which people were asked to choose which of the two prospects they would prefer. The results of those experiments illustrate number of violations of EUT. For example:

$$A : (4000, .80) \text{ or } B : (3000)$$

Most people (80%) chose the prospect B. However in a following problem:

$$C : (4000, .20) \text{ or } D : (3000, .25)$$

the majority of subjects (65%) chose the prospect C over D. This is a violation of EUT as the first choice implies that $.80u(4000) < u(3000)$ while the second one implies $.20u(4000) > .25u(3000)$ which results in reverse inequalities. These choices point out the **certainty effect** in people's decision making. They overweight outcomes that are deemed to be certain, relative to outcomes which are not very much probable. The previous implies that people do not have linear preferences as the EUT states.

[10] Tversky and Kahneman (1974)

When they reversed the problems to negative values, majority seemed to prefer the opposite choice than in the domain of gains. This is called the **reflection effect** and it implies risk aversion in the domain of gains and risk seeking in the range of losses.

Consider the following problems:

In addition to whatever you own, you have been given 1000. You are now asked to choose between $A : (1000, .50)$ and $B : (500)$

In addition to whatever you own, you have been given 2000. You are now asked to choose between $C : (-1000, .50)$ and $B : (-500)$

Most people chose B over A (84%) and C over D (69%). These problems confirm the reflection effect. However in terms of final states both problems are identical. Subjects completely neglected the bonus from their decision making as it was common for both options. We can observe that people do not consider final states when choosing between prospects, they rather think about them as **changes of wealth**.

According to the prospect theory there are two stages of the choice process: **editing phase** and **evaluation**.

In the **editing phase** the prospects are somehow simplified to provide the basis for deciding between them. The outcomes and probabilities are transformed using following operations:

- *Coding.* As already stated people weigh prospects in the form of gains and losses as already stated. The **reference point** - the current state of wealth - from which the changes of wealth are perceived has to be chosen. The formulation of the offered prospects influences the location of the reference point.

- *Combination.* The probabilities of identical outcomes are aggregated together.

- *Segregation.* Risk free components are segregated from the prospect.

- *Cancellation.* When choosing between prospects common elements are disregarded.

After editing phase, the decision makers **evaluate** each edited prospect and choose the one with the highest value. For evaluating the prospects, they assign a decision weight $\pi(p)$ to each probability p and a value $v(x)$ to each outcome x.

The original version of PT introduced by Kahneman and Tversky in 1979 is designed for risky prospects with small number of outcomes. Given a gamble $(x, p; y, q)$ people value the mixed prospect (a prospect with both positive and negative outcomes) according to the equation:

$$V(x, p; y, q) = \pi(p)v(x) + \pi(q)v(y) \tag{3.4}$$

Kahneman and Tversky (1979) proposed hypothetical value and weighting functions as seen in the Figure 3.1 bellow.

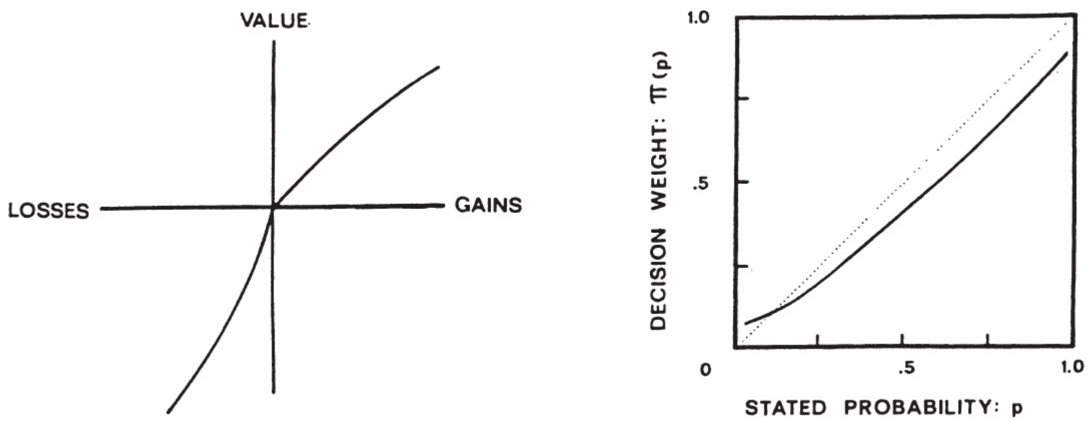

Figure 3.1: Kahneman and Tversky (1979): **Hypothetical value (left) and weighting (right) functions**

The value function is concave for gains (which reflects risk aversion in the domain of gains) and convex for losses (risk seeking in the domain of losses)[11]. The fact that the function is steeper for losses than for gains represents a feature known as **loss aversion**. This feature is depicted in Figure 3.2 showing that the same value h (in absolute terms) has a higher value (utility) in the domain of losses than in the

[11] Tversky and Kahneman (1992)

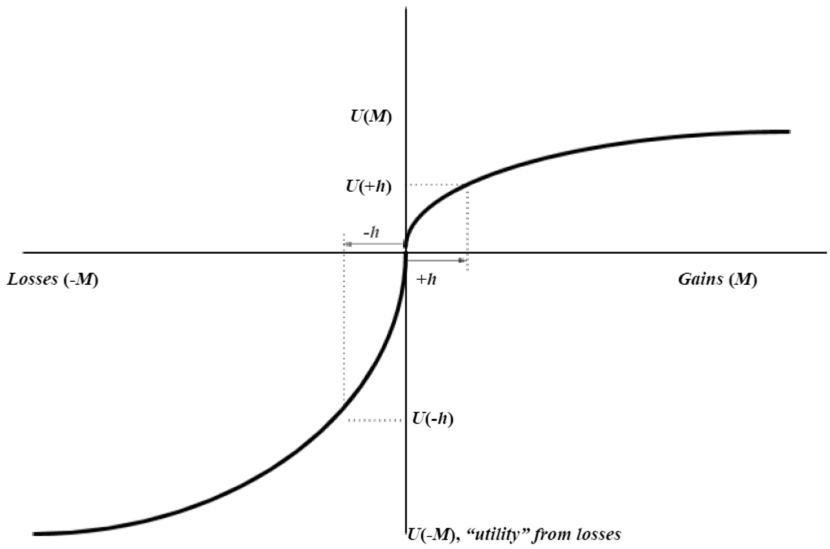

Figure 3.2: **Asymmetric value (utility) function**

domain of gains. Thus when the gamble $(-100, 1/2; 110, 1/2)$ is offered to people most of them rejects as they indicate a greater sensitivity to losses than to gains.[12]

The weighting function represents a nonlinear transformation of the probability range which over weighs very small probabilities whereas under weighs moderate and high probabilities.[13] Hence, $\pi(p)$ is not a "probability measure" and $\pi(p)+\pi(1-p)$ is typically less than one.[14]

In 1992 Kahneman and Tversky presented a new version of the prospect theory which incorporates cumulative instead of individual probabilities in the model and allows for an application of the theory for not only risky, but also uncertain prospects with various numbers of outcomes - called Cumulative prospect theory (CPT).

This model evaluates negative and positive outcomes separately as there is a different sensitivity of subjects to both gains and losses. Let x_i be an outcome and let's assume that $x_i > 0$ are considered as gains, $x_i < 0$ as losses and each prospect includes $x_0 = 0$ which serves as a reference point. It holds that $x_i > x_j$ if $i > j$. Each prospect is a function $f(s) = x$ (s is a state of nature) which is represented by

[12] Barberis (2013)

[13] Tversky and Kahneman (1992)

[14] Tversky and Kahneman (1992)

a pair (x_i, A_i) that yields x_i if A_i occurs. The positive part of f is:

$$f^+(s) = f(s) \text{ if } f(s) > 0 \text{ and } f^+(s) = 0 \text{ if } f(s) \leq 0 \tag{3.5}$$

The negative part $f^-(s)$ is given by similar definition.

The value of a prospect f equals to $V(f)$ satisfying that $V(f) \geq V(g)$ if f is preferred or indifferent to g. It holds that

$$V(f) = V(f^+) + V(f^-) \text{ and} \tag{3.6}$$

$$V(f^+) = \sum_{i=1}^{n} \pi_i^+ v(x_i), V(f^-) = \sum_{i=-m}^{0} \pi_i^- v(x_i) \text{ and} \tag{3.7}$$

$$\pi^+(f^+) = (\pi_0, ..., \pi_n^+) \text{ and } \pi^-(f^-) = \pi_{-m}^+, ..., \pi_0^-) \tag{3.8}$$

When a prospect $f = (x_i, A_i)$ is given by a probability distribution $P(A_i) = P_i$, it can be transformed into a risky prospect (x_i, P_i) with decision weights defined as follows:

$$\pi_n^+ = w^+(P_n), \pi_{-m}^+ = w^-(P_{-m}) \tag{3.9}$$

$$\pi_i^+ = w^+(P_i) - w^+(P_i^*), 0 \leq i \leq n-1 \tag{3.10}$$

$$\pi_i^- = w^-(P_i) - w^-(P_i^*), 1-m \leq i \leq 0 \tag{3.11}$$

where w^+ and w^- are strictly increasing functions that assign to each probability a weight from $[0, 1]$ and satisfy that $w^+(0) = w^-(0) = 0$ and $w^+(1) = w^-(1) = 1$

"$P_i(P_i^*)$ is the probability that the prospect will yield an outcome at least as good as (strictly better than) x_i."[15]

Under the CPT, the **value function** is represented by a two-part power function as follows:

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0 \end{cases} \tag{3.12}$$

The **weighting function** is divided into two functional forms as there are different parameters for losses and gains:

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}, w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} \tag{3.13}$$

[15]Barberis and Thaler (2003)

Using a nonlinear regression procedure KT (1992) estimated the parameters of value and weighting function as follows:

- The median value of the exponent in the value function was the same for gains and losses: $\lambda = \beta = 0.88$. This value confirms the "**diminishing sensitivity**".
- The median λ was estimated to be 2.25 which is in accord with loss aversion theorem.
- Lastly, the median values in the weighting function were $\gamma = 0,61$ and $\delta = 0,69$.

Authors of the theory emphasize that the estimation of a complex model like PT is very problematic and hence they mainly focused on the qualitative features of their dataset rather than on the estimation of the model parameters and measurement of goodness of fit.

Figure 3.3 illustrates the weighting functions of gains (w^+) and losses (w^-) which follow the estimated values of the parameters.

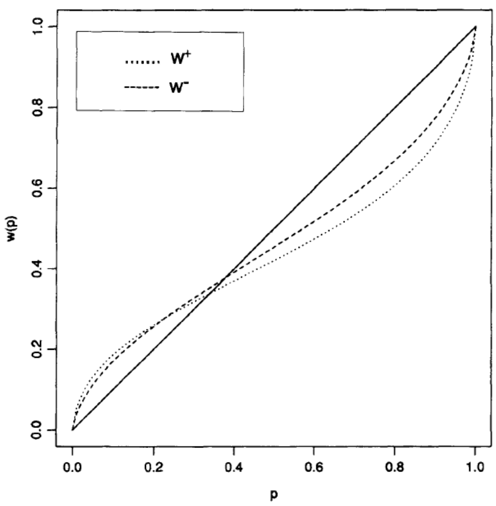

Figure 3.3: Tversky and Kahneman (1992): **Weighting functions for gains and losses**

Chapter 4

Prospect theory: evidence from the field

The prospect theory can be applied in a wide range of fields. Even though this work focuses on applying the PT in finance, the following briefly presents evidence from other fields to provide the reader the overall conception of the matter.

4.1 Prospect theory in various fields

Camerer (2004) mentions various applications of PT:

Labor supply. It is observed that cab drivers - especially the inexperienced ones - do not work more hours if the wage temporarily increases (i.e. during busy days). They set a fixed sum of money which they want to earn each day and after reaching the target, they go home. The cab drivers are averse to any losses compared to this target but on the other hand, any gains have gradually less marginal utility. Decisions of the cab drivers do not follow standard model of the EUT.

Asymmetric price elasticity of consumer goods. According to number of studies consumers - as they are loss averse - tend to have asymmetric responses for price changes. When a price of a good increases, they reduce the amount of the goods purchased more than they would increase their purchases when a comparable price fall occurs.

Saving and consumption Standard life-cycle theory assumes that people - based on the predictions about their future income and accounting for their current income - will spread equally this total income over their lifetime. As people usually earn more money as they are getting older it would mean that they spend larger part of their salary when they are young - running into debt if necessary - and smaller part when they are older - paying back the loan from their youth. However the opposite is often true. Consider a reference-dependent utility of workers: the marginal utility from consuming in a way to exactly reach the reference point is much higher than the marginal utility from consuming above the point (loss aversion). Setting of a reference point follows from the previous consumption and previous levels of the reference point.

Racetrack betting: The favorite-longshot bias. Longshots - horses with a small probability of winning the horse race - are mostly "overbet" compared to favorites - horses with a high probability of winning - who are mostly "underbet". This phenomenon can be explained by PT's certainty effect when people tend to overweight low probabilities.

Racetrack betting: The end of the day effect. The favorite-longshot bias occurs especially at the end of the racing day. Summing up all profits and losses of the day, most bettors are in red numbers "by the last race of the day". According to the PT, the bettors use a daily zero profit reference point and thus the feeling from closing their account in a loss is so strong that they rather take the chance of a small bet on a longshot which could bring a profit enough large to cover all the losses of the day than taking the risk of betting on a favorite.

State lotteries. Large win together with over weighting of low probabilities is the feature of the PT which makes the state lotteries highly attractive for a significant share of the population.

4.2 Prospect theory in finance

Barberis (2013) divides the application of the PT in finance into three branches:

4.2.1 The trading of financial assets over time - the disposition effect

The disposition effect refers to a puzzle exploring why investors tend to keep badly performing stocks (the ones which have fallen in value) too long and sell well performing stocks too soon. This kind of behavior is not rational as stocks which have recently risen in their value have an inclination to continue to perform well and vice versa. Applying the value function $v(.)$ to the data seems to explain the effect. As a poorly performing stock brings the investor to losses compared to its purchasing price and the value function has a convex shape in the domain of losses he becomes risk seeking and thus he keeps the instrument taking the chance of a better performance in the future.

Barberis (2013) states that despite the promising idea the issue is not fully explored yet and a number of papers have concluded that for the argument to work, the value function would need to be much more convex than it was proved to be by the experimental documentation.

4.2.2 The cross section of average returns

This area of research explores why certain groups of securities have higher average returns than other ones. Barberis and Huang (2008) studied the pricing of financial securities considering investors with PT preferences. They showed that a positively skewed security can become overpriced if the probability weighting of the PT is applied.[1] If the instrument is skewed enough, investors can take a substantial position in that security as they overweight the small probability of the security to outperform. Thus the lottery-seeking investors are willing to pay a very high price for these kinds of stocks leading to lower average returns.

[1]The price of the skewed security is compared with the price which would be set by investors with EUT preferences.

The same approach can also be applied to explain the low long-term average return of stocks conducting an initial public offering compared to the return of the stock of a similar firm which does not undertake an offering. It is observed that those initial public offering stocks are significantly positively skewed which again leads to their overpricing and subsequent low average returns.

4.2.3 The aggregate stock market

The equity premium puzzle

Bernatzi and Thaler (1995), BT henceforth, state that "the equity premium puzzle refers to the empirical fact that stocks have outperformed bonds over the last century by a surprisingly large margin". The difference between the annual real returns on stocks and "fixed income securities" such as treasury bills has been significantly high during the whole past century: the former has been on average around 7 percent, whereas the latter only below 1 percent.[2] According to BT (1995), the excessively high margin is given by the loss aversion of investors who demand much higher premium for holding risky stock than the EUT would expect.

The volatility puzzle

As stated at the beginning of this thesis the excessive volatility of returns, its distribution and behavior are considered to be serious puzzles since it systematically violates the EMH and yet there is no unambiguous explanation of those puzzles. Here it follows a couple of belief-based arguments which attempt to explain some of the features of volatility.[3]

- A possible argument for excessive volatility of returns and price-dividend ratios is that investors believe that the volatility of the mean dividend growth rate is much higher than it is in real. Thus when a burst of dividends occurs investors rush into the conclusion that the mean dividend growth rate has risen and

[2] Bernatzi and Thaler (1995)

[3] The arguments come from Barberis and Thaler (2003); they focus on stock returns behavior, but - excluding the first one - it is easily applicable also on futures returns.

they push the prices of stocks up compared to the dividends. Therefore the volatility of returns increases as well.

The argument follows the logic of representativeness and law of small numbers where people neglect the size of the sample and rely on a short piece of data.

- The next illustration describes how overconfidence can lead to an excessive volatility. Assume that an investor identifies certain public information as useful for his investments. Afterwards, he searches for more facts and creates a theory about which he becomes overconfident as he believes it is unique and flawless. If the information that he has gathered is positive he again pushes the prices up too high leading to the increase of volatility.
- The last example adopts the same argument as the first one: the representativeness. Investors may also over rate the fact that past returns have been rising for some time now and they tend to conclude too quick that the future returns will still grow as well. The final influence on volatility is analogous to the previous cases.

4.3 Prospect theory: testing if it holds

An important question is if the theory actually holds in practice: do all participants in the market have preferences according to the PT? Can we rely on the predictions of the PT in financial markets?

Empirical evidence of the PT originates from laboratory experiments conducted using only students as respondents.[4] For example, Edwards (1996) overviews the literature which examined the features of the PT in laboratory conditions as well as used the model for further investigation and concludes that those results generally support the CPT. This kind of sample is however too limited and thus various papers test if it holds also for financial professionals. The authors of those papers extrapolated diverse conclusions.

[4] Abdellaoui, Bleichrodt and Kammoun (2011)

List (2004) investigated 375 subjects actively participating in a "well-functioning marketplace" and in his experiment he shifted the endowment points across agents and evaluated the individual trading rates. He concluded that individual trading rates for inexperienced consumers were in line with the PT whereas experienced individuals' behavior rather followed the EUT. He claims that consumers learn to overcome the endowment effect and alleviate the deviations from rationality not only in situations which they have already experienced, but also in problems beyond their existing experience. Myagov and Plott (1997) as well as van de Kuilen and Wakker (2006) came to the same conclusions: when subjects have the chance to learn by both experience and thought, their choices follow the expected utility maximization.

On the contrary, Abdellaoui, Bleichrodt and Kammoun (2011) conducted an experimental study with 46 financial professionals from US and Lebanon and indeed observed risk aversion for gains and risk seeking for losses and overall loss aversion. However those financial professionals were less averse to losses than what was typically recognized in studies with students. A relevant part of the sample showed to be, in fact, gain seeking, the exact opposite of loss averse subjects predicted by the PT. This kind of finding was linked to the financial crisis which could cause that the subjects ignored the possibility of losses.

A common argument against behavioral finance claims that the financial professionals (the rational traders or arbitrageurs) - as they follow the EUT model - always correct the biased price of an instrument by a process called an arbitrage. The behavioral finance argues that there are significant limits to arbitrage and thus this process does not pay off in the real life.[5] Indeed, the empirical literature which examines the PT using data from financial markets does confirm the shape of the PT value and weighting function. The shape is however less pronounced than stated by the original model. A similar conclusion was reached by studies focusing on individual behavior as well.

Gurevich, Kliger and Levy (2009) conducted a field study in which they tested CPT at the financial market using US stock option data. "Option prices possess information about actual investors' preferences in such a way that an exploitation

[5]Details about this issue in Chapter 3 of this thesis.

of conventional option analysis, along with theoretical relationships, makes it possible to elicit investor preferences."[6] Gurevich et al. used those data for estimation of both the value function and probability weighting function. The study was performed using options written on individual stocks. The results confirmed the general features of the model, meaning the shape and the properties of the estimated functions. However, quantitatively, both functions were estimated to be more linear than those obtained in laboratory experiments. Moreover, the utility function exhibited less loss aversion than it was attained in laboratory results.

Kliger and Levy (2009) have arrived to the same conclusion when they tested the CPT using index option prices. They investigated the investors' preferences included in the prices of one-month-to-expiration European call options written on the S&P 500 index and they indeed confirmed that security markets are affected by investor psychology and their preferences exhibit nonlinear probability weighting, loss aversion and diminishing sensitivity when moving away from the reference point.

[6] Gurevich, Kliger and Levy (2009), page 1221

Chapter 5

Futures market

This section describes a specific financial market: the futures market. So far a more extensive research has been focusing on showing if PT holds in the stock market but there are not that many studies focusing on the futures market.

After all, the futures market is however a very convenient market where the preferences of investors under uncertainty can be well observed. The trading of futures serves for all of the three hedging, arbitrage and speculation and in this way it conveniently reflects the internalization of financial markets.[1]

5.1 Mechanics of futures market

"A futures contract is an agreement between two parties to buy or sell an asset at a certain time in the future for a certain price. Unlike forward contracts, futures contracts are normally traded in an exchange."[2]

Derivatives markets are generally very liquid as when an investor is interested in taking a short position, it is usually not difficult to find someone who wants to take the long one and vice versa. As already mentioned, the futures markets attract various types of investors: hedgers, speculators and arbitrageurs [3].

Each futures contract has assigned a *delivery month* which varies from contract

[1] Wang (2009)

[2] Hull (2009), page 6

[3] Hull (2009)

to contract. For example, a certain commodity can have delivery months of March, May, July, September, and December. Most of the contracts do not lead to the delivery itself since the majority of traders usually close out their positions before the delivery month.

When investors invest in a futures contract, they do not need to pay the total value of that contract, but they only have to deposit previously agreed amount of funds in a *margin account*. The amount of the initial payment which has to be paid when the contract is entered into is called the *initial margin*. By *marking to market* the account, the margin account is adjusted to mirror the gains and losses at the end of each trading day. The daily movements of a contract price are limited and they are set by the exchange. These limitations are specified to prevent the speculative traders to bias the price.

The most important difference between options and futures is that in case of futures the possible loss or gain is very large. The reason is that the futures contracts have very *high leverage* meaning they offer highly disproportionate gains or losses compared to the initial margin. For example, an investor enters into a long position of a futures contract on lets say 5,000 bushels of corn valued as 300 cents per bushel. The investor pays an initial margin of 1,500 dollars. If the price of the contract jumps by 5% to 315 cents per bushel, the investor' gain is 750 dollars which represents 50% of the initial margin. On the contrary if the price goes down by 5% the realized loss is 50% of the initial margin.[4] Thus futures contracts are extremely risky derivatives.

The futures price slowly converges to the spot price (the current price) of the underlying asset as the delivery month is approaching. The relationship between futures and spot price as the delivery period is approaching is depicted in the Figure 5.1.

Each futures contract is specified with its size, the exchange that the contract is traded on, the maturity (delivery) month and how the price is quoted. Next, there are certain data which are collected for each trading day of each contract. Those are following:

- **Opening price** is the price at which the contract was traded at the very

[4]Bibliography [22]

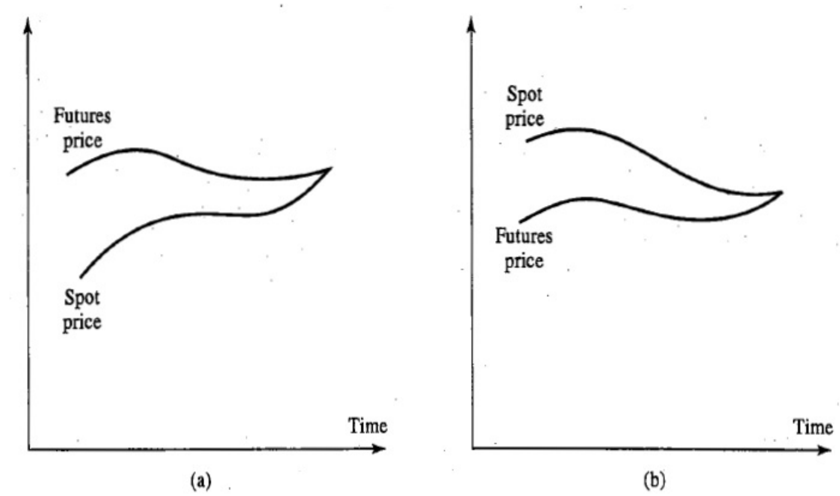

Figure 5.1: Hull (2009): **Relationship between futures price and spot price**

beginning of the day.

- The **highest** and the **lowest** price for which the contract was traded that day.
- **Settlement price** is the price which is applied to the calculation of daily gains or losses. It is usually the price at which the contract was traded right before the end of the trading day.
- **Open interest** is the number of all contracts outstanding. It is the number of long positions or, similarly, of short positions.

Chapter 6

Estimation of volatility of returns on futures contracts

The empirical part focuses on modeling the volatility of returns on futures contracts. It analyzes the volatility of three kinds of futures contracts: a contract on cotton, S&P 500 index and crude oil. Each of them comes from a different area and thus we will be able to compare the extent in which the volatility of different futures contracts is influenced by various factors and make conclusions about the estimated differences.

6.1 Hypotheses

First, this research expects that the volatility of each type of futures contracts exhibits a leverage effect. Negative unexpected shocks (bad news) should have a greater impact on volatility of returns on futures contracts than positive shocks (good news).

Second, it is assumed that an investor sentiment measured using information about the open interest directly reflects the reactions of investors on the market movements. Therefore, it should exhibit an asymmetric leverage effect on the volatility of returns as well.

The corroboration of an asymmetric leverage effect in the data is considered to be a proof of a loss aversion in investors decision making at the given futures markets.

6.2 Methodology

6.2.1 Stationarity test

The basic assumption for every proper analyzes of the time series is the requirement of stationarity of the series. Thus it is necessary to examine the target variable for stationarity. The **augmented Dicky-Fuller test** is performed to check if the variable follows a unit-root process (the null hypothesis) or if it was generated by a stationary process (the alternative hypothesis). The test fits the model:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \beta_1 \Delta y_{t-1} + ... \Delta y_{t-k} + u_t \tag{6.1}$$

by ordinary least squares where k is the number of lags tested and the null hypothesis $\beta = 0$ is equivalent to the statement that the series follows a unit root process.[1]

To allow the analysis of a non stationary variable it is convenient to transform it using the **logarithmic** (log) **difference** of the series which is often stationary and analyze that. In this work the log difference of settlement futures prices (which is equivalent to the return on futures contracts) is applied:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{6.2}$$

where r_t is the daily return on the futures contract at time t, P_t and P_{t-1} are the settlement prices at time t and $t-1$ respectively.

6.2.2 Specification of ARMA model

First of all it is necessary to specify the mean equation in the form in which residuals follow a random walk process (meaning they are white noise, i.e. there is no autocorrelation or partial autocorrelation in the error terms) since it is one of the

[1] Bibliography [39]

basic assumptions of a time series regression. For that there are **autoregressive moving average models ARMA (p,q)**. If the dependent variable is regressed only on a constant, there is often still a significant autocorrelation or partial autocorrelation in the residuals and therefore they are not a white noise. We can filter these effects out by including autoregressive (AR) terms and moving average (MA) terms. ARMA(p,q) is defined as follows:

$$y_t = c + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=1}^{q} b_j u_{t-j} + u_t \tag{6.3}$$

where the first sum is an AR(p) term and the second sum is a MA(q) term.

Testing if residuals follow a random walk process is achieved using **Autocorrelation** and **Partial autocorrelation functions** (ACF and PACF).

ARMA models are estimated using a **maximum likelihood estimation**. If more ARMA models (e.g. ARMA(0,1) and ARMA(1,0)) are appropriate the **Akaike information criterion** (AIC) is employed to decide which of the **non-nested models**[2] is the most appropriate one. It is defined in a following way:

$$AIC = \frac{-2L}{T} + \frac{2k}{T} \tag{6.4}$$

where L is the log-likelihood function, T number of observations and k number of explanatory variables plus 1. The lower the value of AIC is the better the model explains the dependent variable. The first term penalizes for a low likelihood (because than the log-likelihood is in large negative numbers and multiplied by minus it becomes a very high positive number), whereas the second term penalizes for using a higher number of explanatory variables.

To test for the presence of ARCH effects in the final ARMA(p,q) model a **Lagrange Multiplier** (LM) **test** is performed. The squared estimated residuals $\hat{e}_t^2$ from the conditional mean regression (which is defined in equation 6.6) are regressed on the constant and lagged squared residuals (number of lags is given by the tested order of an ARCH model).

$$\hat{e}_t^2 = \gamma_0 + \gamma_1 \hat{e}_{t-1}^2 + ... + \gamma_q \hat{e}_{t-q}^2 + v_t \tag{6.5}$$

[2]Non-nested models are those with a different set of explanatory variables, i.e. it is not possible to set one or more variable to zero to get the other model.

The test statistic equals to TR^2 with $\chi^2(q)$ distribution where T is the number of observations in the auxiliary regression, R^2 is a goodness-of-fit measure and q number of degrees of freedom which corresponds to the number of lags of squared residuals. The null hypothesis $\gamma_1 = ... = \gamma_q = 0$ stands for no ARCH effects in the squared residuals.

6.2.3 ARCH type models

In order to capture all the stylized facts which have been stated in Chapter 2, the financial data are often modeled using non linear models as they better approximate the distribution of financial data than linear models.[3] The following description of ARCH type models follows the approach of Chris Brooks (2008). ARCH (autoregressive conditionally heteroscedastic) models assume that the variance of residuals in the mean equation is not constant over time. Volatility of returns is highly time dependent which follows from the fact that volatility clustering or leverage effects are its common features. Thus ARCH type models fit the data very well.

The conditional mean equation under ARCH(q) model is typically as follows:

$$y_t = \theta_0 + \sum_{s=1}^{n} \theta_s x_{st} + u_t, u_t \sim N(0, \sigma_t^2) \tag{6.6}$$

where x_{st} can be either an ARMA term or any other independent variable and the conditional variance of the error term is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2, \text{where } \alpha_i \geq 0 \ \forall i = 0, 1, 2, ..., q \tag{6.7}$$

Generalized ARCH model (GARCH (p,q)) allows the conditional variance to be dependent also on its own lags as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{6.8}$$

Again, $\alpha_i \geq 0 \ \forall i = 1, 2, ..., q, \ \beta_j, \alpha_0 > 0, j = 1, ..., p.$

The unconditional variance under a GARCH (1,1) specification is given by:

$$var(u_t) = \frac{\alpha_0}{1 - (\alpha_1 + \beta)} \tag{6.9}$$

[3] Brooks (2008)

thus $\alpha_1 + \beta < 1$ to assure that the variance is positive.

The fitted conditional variance σ_t^2 can be interpreted as the weighting function of a long-term average (dependent on α_0), previous periods information about the volatility $\sum_{i=1}^{q} \alpha_i u_{t-i}^2$ (measure of the volatility reaction) and variances from previous periods $\sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$ (measure of the volatility persistence).

Generally, GARCH (1,1) model is considered to be usually better than ARCH models since it captures all of the past squared errors that can influence σ_t^2 meaning that GARCH (1,1) variance can be expressed by substituting previous period's variances by past GARCH (1,1) variances σ_{t-i}^2 where $i = 1, ..., k; k$ is the number of all observations. Thus usually GARCH (1,1) model is sufficient enough to capture the autocorrelated characteristics of such series.

Since GARCH models cannot capture the asymmetric leverage effect and they do not provide any direct implications between the conditional variance and mean, other modifications have been developed. Those models capture the conditional variance as a function of not only magnitude of the lagged residuals, but also of their sign.

The Threshold GARCH model is defined using the conditional standard deviation instead of the conditional variance. Let's assume that $\epsilon_t = \sigma_t Z_t$ and $Z_t \sim IID(0,1)$ and ϵ_t is a real-valued discrete-time process, $\epsilon_{t-1} = (\epsilon_{t-1}, \epsilon_{t-2}, ...)$ the information set (σ-field) of all available information at time t and $\epsilon_t^+ = max(\epsilon_t, 0)$ and $\epsilon_t^- = min(\epsilon_t, 0)$ are the positive and negative parts of ϵ_t. Than:

$$\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i^+ \epsilon_{t-i}^+ - \alpha_i^- \epsilon_{t-i}^- + \sum_{j=1}^{p} \beta_j \sigma_{t-j} \tag{6.10}$$

where $(\alpha_i^+)_{i=1,q}$, $(\alpha_i^-)_{i=1,q}$ and $(\beta_j)_{j=1,p}$ are real scalar sequences.[4] The advantage of modeling the scalar σ instead of the conditional variance is that it is not necessary to set any positivity restrictions on the value of the estimated parameters. Nevertheless, the positivity constraints are often required as it makes the probabilistic analysis much less complicated.

The GJR form of threshold GARCH models (1,1,1) (named after its authors

[4] Zakoian (1994)

Glosten, Jagannathan and Runkle) defines the conditional variance as follows:

$$\sigma_t^2 = \alpha_0 + \alpha u_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 \tag{6.11}$$

where

$$I_{t-1} = \begin{cases} 1 & \text{if } u_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases}$$

The leverage effect is present if $\gamma > 0$. To keep the non-negativity of the variance it has to hold that $\alpha > 0, \beta \geq 0$ and $\gamma + \alpha \geq 0$. Thus it is possible that $\gamma < 0$ as long as the sum of alpha and gamma is bigger or equal to 0.

The exponential GARCH model (EGARCH (1,1,1)) defines the conditional variance as:

$$ln(\sigma_t^2) = \omega + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{\mid u_{t-1} \mid}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] + \beta ln(\sigma_{t-1}^2) \tag{6.12}$$

There is no need for restricting the parameters to non-negative values as the logarithmic form of the equation assures that the variance will be always positive even though the parameters are not. Consequently, the leverage effect is present when $\gamma < 0$.

Likelihood ratio statistic is used to test which of the nested models is the best. It is defined as follows:[5]

$$2(L_A - L_{null}) \tag{6.13}$$

where $L_A(L_{null})$ is the **log-likelihood function** for the alternative (null) model, the statistic follows χ^2 distribution with $(df_A - df_{null})$ degrees of freedom. The null hypothesis is that the null model is more suitable than the alternative one.

6.2.4 Division of the observed period

Since the provided data for all of the three futures contracts are dated from January 4th, 1995 to February 26th, 2016 it is likely that the parameters of the model can differ due to changes in the market conditions during this time. The **Quandt**

[5]Bibliography [52]

Likelihood Ratio (QLR) **test** is performed on the chosen ARMA(p,q) model to detect the highest Chow statistic over the entire sample. The Chow test tests if the estimated parameters of the model are the same for the period before and after a given date at a given confidence interval. The **Chow test statistic** is defined as follows:[6]

$$\frac{(S_C-(S_1+S_2))/k}{(S_1+S_2)/(N_1+N_2-2k)} \tag{6.14}$$

where S_1 (S_2) is the sum of squared residuals from the first (second) group, N_1 and N_2 are number of observations in each group and k is the total number of parameters. The Chow statistic follows F distribution with k and (N_1+N_2-2k) degrees of freedom.

6.2.5 News impact curve

The **news impact curve** is - in this thesis - adopted for asymmetric models to graphically capture the leverage effect. "It plots the response in the conditional variance, σ_t^2, to an innovation in the standardized error term, z_{t-1}. When calculating the response in σ_t^2 historical conditional variances $(\sigma_{t-i}^2, i>0)$ are set to σ^2 and historical error terms $(z_{t-i}, i>1)$ are set to 1. The default value for σ^2 is an estimate of the unconditional variance, the mean of the estimated conditional variances. Finally error terms that enter in the conditional variance formula are obtained as $e_t=\sigma z_t$."[7]

6.2.6 Investor sentiment

Wang(2009) defines the **investor sentiment index** using open interest information:

$$SI_t=\frac{Open_t-minOpen_i}{maxOpen_i-minOpen_i} \tag{6.15}$$

where $Open_t$ is the value of open interest at time t, $minOpen_i$ ($maxOpen_i$) is the minimal (maximal) value of open interest over the period i. Therefore the index expresses a value from the interval $[0,1]$ and the higher the value is the higher the

[6]Bibliography [49]

[7]Bibliography [9]

"attractiveness" of the futures contracts is. In this work the $(\Delta SI_{t-1})^2$ is used to measure the volatility of investor sentiment. Thus the coefficient on that term captures "the effect of the magnitude of the shifts in sentiment on volatility formation within the futures market."[8]

6.3 Data specification

For the analysis of futures volatility the research uses continuous futures contracts (CFC) which are constructed by assembling together individual contracts. It allows us to analyze a long-term history of futures price development. The individual contracts have a short existence as well as variable liquidity (they are often left "untraded" for the first months of their "life") which make them unsuitable for a long-term trend analysis.[9]

There are various data sets of CFC for the same commodity depending on the method of chaining the contracts together. Number one #1 is assigned to a method which uses front month contracts - those that are closest to their expiry date - which are typically the most liquid ones.

This research uses CFC #1 since even though the commodities possibly exhibit seasonal effect and thus have a term structure (they strongly depend on expiry date), those term structure effects tend to even out over a longer period, say 5-10 years.[10]

This research divide over 20 years of observations in more periods depending on the QLR test. The work analyses the periods separately for each commodity. It uses settlement prices for each trading day from January 4th, 1995 to February 26th, 2016.

Here follows the detail description of each commodity, the data and its specifications.

[8] Wang (2009)

[9] Bibliography [33]

[10] Bibliography [33]

6.3.1 Cotton

Cotton is one of the basic crops which is used in textile, agriculture and food industries. The three largest producers of cotton in the world are China, India and USA with production of 6.532, 6.423 and 3.553 millions of tunes in crop year 2014/2015 respectively.[11] China is not only its biggest producer, but also consumer[12]. On the other hand USA is typically the largest exporter of cotton in the world.

In the crop year of 2009/2010, floods in major areas of cotton production (Australia, Pakistan and China)[13] have caused a significant decrease in supply, thus caused an excess of demand (which was soaring in China - biggest consumer of cotton in the world) over supply and thus the prices of cotton and consequently cotton futures contracts prices went sharply up. It had a huge impact on the market. It was a convenient change for farmers whereas for manufactures it was mostly harmful.[14] After this crush - to support the local producers - China started to support the domestic and world prices over the market clearing level, which have led to huge stocks of cotton piling up in China. Thus the prices went sharply down as the world stockpile equaled to 3 pairs of jeans for every person in the world.[15] In 2014/2015 China has changed the policy and shifted to income support and thus the stocks again started to slowly reduce.[16]

The cotton futures provided for this research were traded at ICE (International commodity exchange). The size of one contract is 50,000 pounds of net weight and the prices are quoted in cents and hundredths of a cent per pound. The contract months of the cotton futures are March, May, July, October and December.

6.3.2 S&P 500 index

S&P 500 index (Standard & Poor's 500 stock index) is created by 500 individual stocks which were chosen based on the market size, liquidity, industry grouping and

[11] Bibliography [40]

[12] Bibliography [8]

[13] Bibliography [42]

[14] Bibliography [5]

[15] Bibliography [20]

[16] Bibliography [45]

many other criteria. It is considered to be a leading indicator of U.S. equities which reflects risk and return characteristics of "large cap companies" (the companies with a large market capitalization).[17]

The S&P 500 futures provided for this research were traded within a CME group (Chicago Mercantile Exchange & Chicago Board of Trade) in the form of a big contract of which value equals to $250 times the quoted futures price. The contracts were listed quarterly, i.e. in March, June, September and December.

6.3.3 Crude oil

The largest producers of crude oil in the world are United States, Saudi Arabia, Russia and China in this order in 2013.[18] "OPEC (The Organization of the Petroleum Exporting Countries) is a permanent, intergovernmental Organization, created at the Baghdad Conference on September 10–14, 1960, by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. OPEC's objective is to co-ordinate and unify petroleum policies among Member Countries, in order to secure fair and stable prices for petroleum producers."[19] More than 80% of current oil reserves are located in OPEC countries. Thus its decisions highly effect the U.S. and worldwide crude oil prices.

Since 1995 to 1997 the price of crude oil had a steady growth. In 1997 Asian oil demand was hit by a severe economic crisis and it crashed in 1998. In 1998 OPEC significantly increased its production quota. These two events combined together caused an oil price downturn. Since than OPEC attempted to increase the prices again by setting more and more cuts of production which along with other factors slowly increased the oil price through 1998 to 2001. In response to the September 2001 terrorist attack the prices decreased again and the recovery consequently slowed down.[20]

The Venezuelan oil workers strike in 2003 along with invasion of Iraq caused low world inventories. An improving economy accompanied by increase of U.S. as

[17] Bibliography [23]

[18] Bibliography [24]

[19] Bibliography [32]

[20] Bibliography [53]; Belaunde (2001)

well as Asian demand drove an excessive demand which led to the period of rapidly increasing prices. In 2008 the world economic crises hit the entire economy and right after its beginning the extremely high speculation on the futures market along with the decreasing inventory contributed to a historically highest price of crude oil at the level of $147.30 in July, 2008. The recession had soon an effect on decreasing demand which led to a deep downturn of oil prices right after its peak. Another OPEC cut in 2009 and a rising demand in Asia caused the price to rise again.[21] The 2014 price drop is caused among other factors again by a low demand due to a weakened economic activity, the increased geopolitical risk due to troubles in Iraq and Libya and unwillingness of Saudis to attempt to strengthen the price.[22]

The crude oil futures provided for this research were traded within a CME group. The size of one contract is 1,000 barrels of crude oil and the prices are quoted in U.S. dollars and cents per barrel. The contract months of the crude oil futures are changing over the sample period.

6.4 Results

6.4.1 Cotton

First of all it is necessary to assess the stationarity of the time series. As seen from the Dickey fuller stationarity test in Table 6.1 the series of settlement prices is non stationary. Nevertheless the log difference of the series (returns) proved to be stationary and thus the analysis is performed using the log difference of the futures prices series or in other words returns. In the Figure 6.1 the cotton futures prices and returns are depicted to graphically show the stationarity of both series.

The QLR test performed on AR(1) model[23] showed the highest Chow statistic in February 22nd, 2008 and May 18th, 2010 with the second date having the highest Chow statistic in the sample. Thus the overall number of observations (5,053) is

[21] Bibliography [53]; Belaunde (2001)

[22] Bibliography [41]

[23] AR(1) model was the most suitable one in the entire sample. Next, a different ARMA model for each period was chosen.

Table 6.1: **Stationarity test for cotton futures prices and returns**

	Test Statistic	5 % critical value	p-value
Settlement price	-2.482	-2.860	0.120
Return	-67.671	-2.860	0.000

Source: Author's results

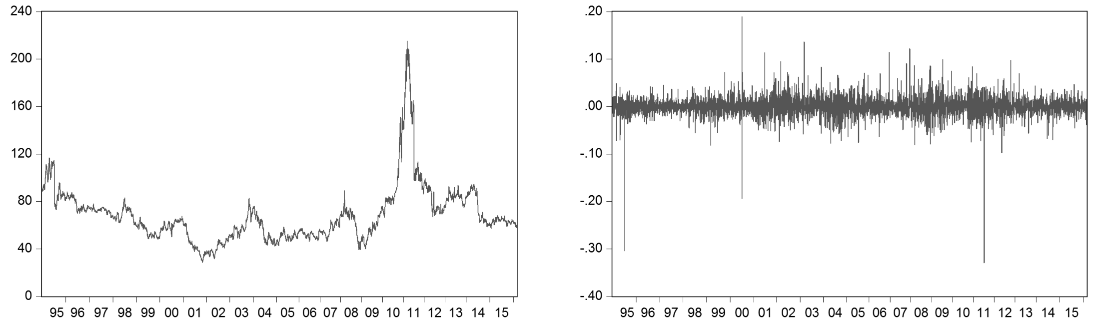

Figure 6.1: **Settlement prices (left) and returns (right) of cotton futures**

divided into 3 periods of 3,210, 491 and 1,352 observations. The difference between the coefficients of the model using observations until 2008 and those between 2008 and 2010 could be explained by the Great recession which in U.S. started in December 2007 and ended in June, 2009.[24] In this period the unexpected news and investors concerns and conservatism could seriously influence the futures market. The 2010 shift could be triggered by the unexpected floods in major production areas and the consequent events.

Figure 6.2 depicts the distribution of the returns in each period plotted against the normal distribution. It exhibits **fat tails** and **high peaks** as assumed by the theory.

For the first period, ARMA (0,0) was the first suitable model where residuals became a white noise. The square residuals are on the other hand highly correlated as seen from the ARCH LM test where the null hypothesis was highly rejected with the p value very close to zero (TR^2 equals to 34.664, 5 degrees of freedom).

For the second and third period, ARMA (0,0) and ARMA (1,1) respectively

[24]Bibliography [50]

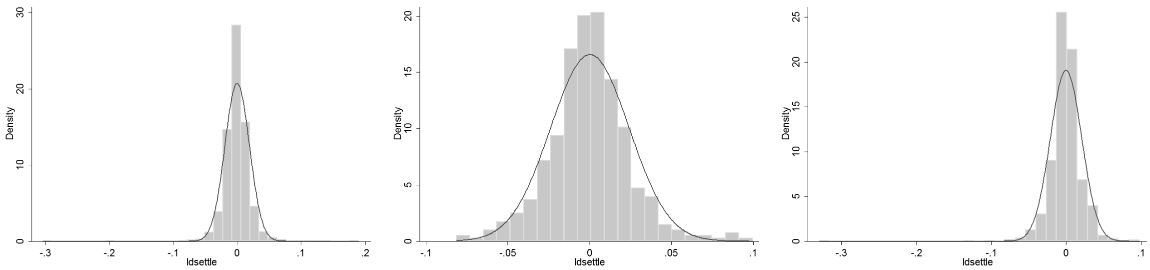

Figure 6.2: **Distribution of cotton futures returns**

were chosen. The square residuals are again highly correlated (the values of TR^2 are 18.805 and 82.233 respectively).

The results of the final selected ARCH type models in each period are recorded in Table 6.2.[25] Those models are considered - based on the Likelihood ratio test and AIC criterion for non-nested models - to be the best estimations of the conditional variance for the provided data with residuals which follow the random walk (assessed by ACF and PACF functions). In the entire work the **p-value** of each parameter is stated in the parenthesis under it.

Table 6.2: **Cotton: Assessing the best ARCH model**

σ_t^2	const	α_1	α_2	α_3	LL	AIC
First period						
TGARCH (1,1)	.0000359 (0.004)	.0396791 (0.000)	-.008815 (0.004)	.974055 (0.000)	8288.903	-16567.81
Second period						
TGARCH (1,1)	.0003306 (0.172)	.0564157 (0.001)	-.0234175 (0.201)	.9514877 (0.000)	1151.318	-2292.637
Third period						
EGARCH (1,1)	-.6575253 (0.000)	-.0627179 (0.000)	.2719883 (0.000)	.9156593 (0.000)	3529.076	-7046.151

Source: Author's results

[25] TGARCH (1,1) is in Stata - the statistical software used for the analysis - defined as follows: $\sigma_t = \alpha_0 + \alpha_1 \mid \epsilon_{t-1} \mid + \alpha_2 \mid \epsilon_{t-1} \mid I_{t-1} + \alpha_3 \sigma_{t-1}$ where $I_{t-1} = 1$ for $\epsilon_{t-1} > 0$ and 0 otherwise. Thus for negative leverage effect $\alpha_2 < 0$. Other models are defined according to the theory stated in the section 6.2.

In all periods the negative coefficient on the asymmetric term (α_2 in case of TGARCH and α_1 in case of EGARCH) implies the presence of a **leverage effect** meaning that the negative unanticipated news are more destabilizing than the positive ones. For example, in the first period $\alpha_2 = -0,0088$ means that the volatility today is lower if yesterday news were good than when they were bad. In the first and third period the term is highly significant which corresponds to the assumed relationship of a **loss aversion**. The graphical representation of the leverage effect is depicted in Figure 6.3.

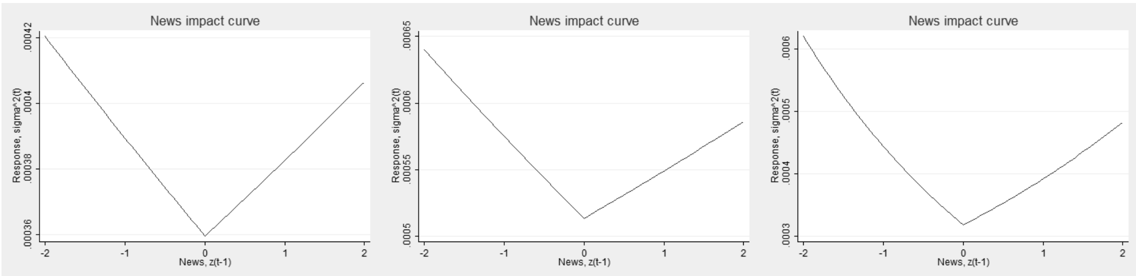

Figure 6.3: **Cotton: News impact curves in the first, second and third period starting from the left**

The term α_3 in both the TGARCH and EGARCH model expresses the volatility persistence and in all three periods it is very high (close to 1) and significant which indicates that the shocks take a long time to dissipate and confirms the presence of **volatility clustering** in the data.

When a sentiment index was included in the conditional variance equation the parameters have changed significantly as seen in Table 6.3. In TGARCH(1,1) models the index was integrated in the following way:

$$\sigma_t = \alpha_0 + \alpha_1 \mid \epsilon_{t-1} \mid + \alpha_2 \mid \epsilon_{t-1} \mid I_{t-1} + \alpha_3 \sigma_{t-1} + \beta_1 \mid \Delta SI_{t-1} \mid i_{t-1} + \beta_2 \mid \Delta SI_{t-1} \mid \tag{6.16}$$

where $I_{t-1} = 1$ for $\epsilon_{t-1} > 0$ and 0 otherwise and $i_{t-1} = 1$ for $\Delta SI_{t-1} < 0$ and 0 otherwise. The EGARCH (1,1) model is adjusted in a following way:

$$ln(\sigma_t^2) = \alpha_0 + \alpha_1 \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha_2 \left[\frac{\mid u_{t-1} \mid}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \alpha_3 ln(\sigma_{t-1}^2) + \beta_1 \Delta SI^2 i_{t-1} + \beta_3 \Delta SI^2 \tag{6.17}$$

Table 6.3: **Cotton: Assessing the best ARCH model with SI dummy**

σ_t^2	const	α_1	α_2	α_3	$\Delta SI \leq 0$	$\mid \Delta SI \mid$
First period						
TGARCH (1,1)	-8.259684 (0.000)	.5970891 (0.000)	-.2979185 (0.000)	.095966 (0.049)	-6.98022 (0.000)	4.333789 (0.000)
LL: 8296.519 ; AIC: -16579.04						
Second period						
TGARCH (1,0)	-7.705067 (0.000)	.391449 (0.000)	-.0159685 (0.872)	-	-2.871124 (0.362)	2.303123 (0.121)
LL: 1148.789 ; AIC: -2285.578						
Third period						
EGARCH (1,1)	-1.966045 (0.000)	-.0686643 (0.005)	.4286489 (0.000)	.7585361 (0.000)	-3.643893 (0.019)	2.690323 (0.000)
LL: 3571.151 ; AIC: -7126.302						

Source: Author's results

The parameters on the sentiment index are significant in the first and third period. In the first - relatively calm - period the change of the sentiment index has a significant positive effect on the volatility - any change in SI increases the volatility of returns. The negative change of SI has a significant negative effect on the volatility meaning that if the change is negative the volatility of returns decrease. In the third period (period in which natural conditions led to excessive demand and soon a consequent policy to the excessive supply) any increase of SI volatility again increases the volatility of returns whereas the increase of SI volatility decreases the volatility of returns when there is a negative change in SI. In both periods the asymmetric effect over weighs the symmetric one meaning the overall volatility changes according to the sign of the asymmetric term. The leverage is very strong. The power of the sentiment terms is almost twice larger in the first relatively calm period. However the estimated results are not in accordance with the assumed relationship.

6.4.2 S&P 500 index

Again, as seen in Table 6.4 and Figure 6.4 the stationarity test showed that the futures returns are more convenient for the analysis.

Table 6.4: **Stationarity test for S&P 500 futures prices and returns**

	Test Statistic	5 % critical value	p-value
Settlement price	-1.555	-2.860	0.5061
Return	-76.561	-2.860	0.000

Source: Author's results

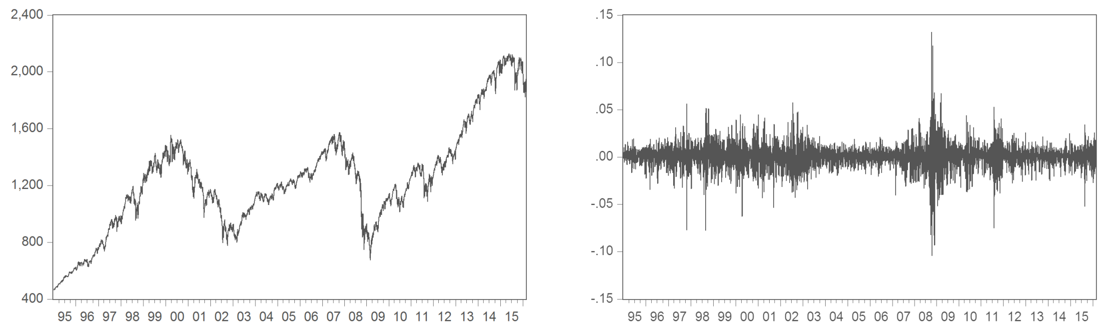

Figure 6.4: **Settlement prices (left) and returns (right) of S&P 500 futures**

The QLR test performed on ARMA(4,3) model showed the highest Chow statistic in October 23rd, 2008. The overall number of observations (5,310) is divided into 2 periods of 3,471 and 1,839 observations. The difference between these two periods could be explained by consecutive recession and change of the market expectations after the Great recession. As the S&P 500 index is considered to represent the entire U.S. market the changes of the whole economy in the recession could harm the S&P 500 futures market.

As seen in the Figure 6.5 the distribution of the returns in each period plotted against the normal distribution again exhibits **fat tails** and **high peaks**.

For the first and second period, ARMA (2,0) and ARMA (4,4) respectively were chosen to model the conditional mean. The square residuals are again highly

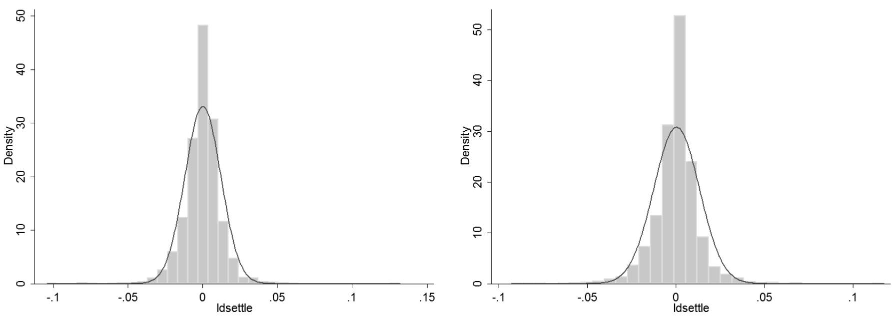

Figure 6.5: **Distribution of S&P 500 futures returns**

correlated as seen from the ARCH-LM test (the values of TR^2 are respectively 850.673 and 373.489).

Table 6.5: **S&P 500: Assessing the best ARCH model**

σ_t^2	const	α_1	α_2	α_3	LL	AIC
First period						
TGARCH (1,1)	.0001753 (0.000)	.1349257 (0.000)	-.1366409 (0.000)	.9320491 (0.000)	11164.25	-22312.49
Second period						
TGARCH (1,1)	.0003576 (0.000)	.2221721 (0.000)	-.2361983 (0.000)	.8902552 (0.000)	5911.071	-11796.14

Source: Author's results

We can see in Table 6.5 that in both periods the negative coefficient on the asymmetric term implies the presence of the **leverage effect** again. The term is highly significant which again corresponds to the assumed relationship of a **loss aversion**. The graphical representation of the leverage effect is depicted in Figure 6.6. The power of the asymmetric effect is in both periods by some decimal points larger than the symmetric one meaning that the asymmetric effect dominates the symmetric one and indicating a strong leverage effect.

The term α_3 which expresses the volatility persistence is very high and significant and thus indicates that the shocks take a long time to dissipate and confirms the presence of the **volatility clustering** in the data.

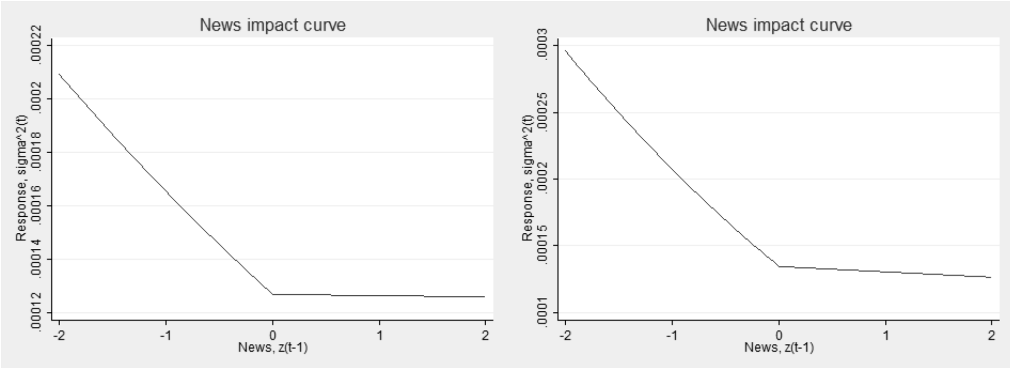

Figure 6.6: **S&P 500: News impact curves in the first and second period starting from the left**

Table 6.6: **S&P 500: Assessing the best ARCH model with SI dummy**

σ_t^2	const	α_1	α_2	α_3	$\Delta SI \leq 0$	$\mid \Delta SI \mid$
First period						
TGARCH (1,1)	-13.13336 (0.000)	.1433843 (0.000)	-.1490415 (0.000)	.9375246 (0.000)	6.146842 (0.784)	-3.017156 (0.882)
LL: 11102.33 ; AIC: -22186.9						
Second period						
TGARCH (1,1)	-12.60944 (0.000)	.2059686 (0.000)	-.1569056 (0.000)	.8833658 (0.000)	-20.20614 (0.247)	7.985285 (0.000)
LL: 5869.643 ; AIC: -11709.29						

Source: Author's results

The parameter on the sentiment index is significant only in the second period and only on the symmetric term as seen in Table 6.6. Therefore, the change of the sentiment index has again a significant positive effect on the volatility - any change in SI increases the volatility of returns.

6.4.3 Crude oil

Again, as seen in Table 6.7 and Figure 6.7 the stationarity test showed that the futures returns are more convenient for the analysis.

The QLR test performed on ARMA(2,2) model showed the highest Chow statistic

Table 6.7: **Stationarity test for crude oil futures prices and returns**

	Test Statistic	5 % critical value	p-value
Settlement price	-1.688	-2.860	0.4374
Return	-76.113	-2.860	0.000

Source: Author's results

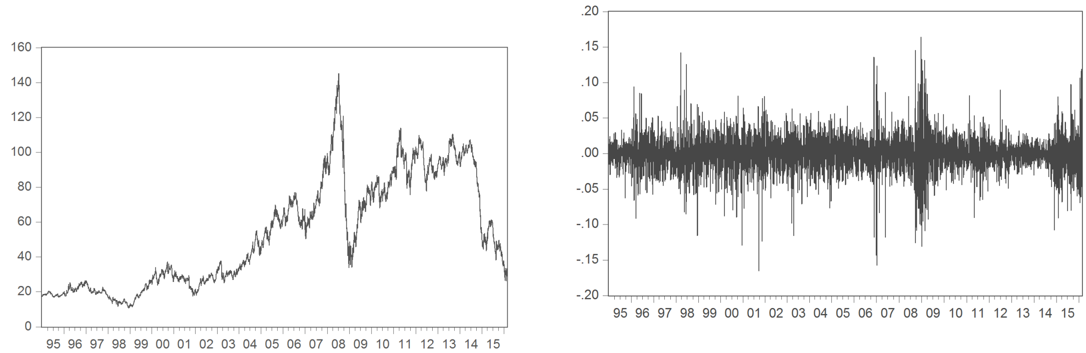

Figure 6.7: **Settlement prices (left) and returns (right) of crude oil futures**

in November 16th, 2001. The overall number of observations (5,312) is thus divided into 2 periods of 1,722 and 3,590 observations. The difference could be explained by the change of the price reactions and evolution in response to the increasing demand and decreasing inventories after 2002 and a lot of following influential events mentioned in subsection 6.3.3.

The distribution of the returns in each period depicted in Figure 6.8 again exhibits **fat tails** and **high peaks**.

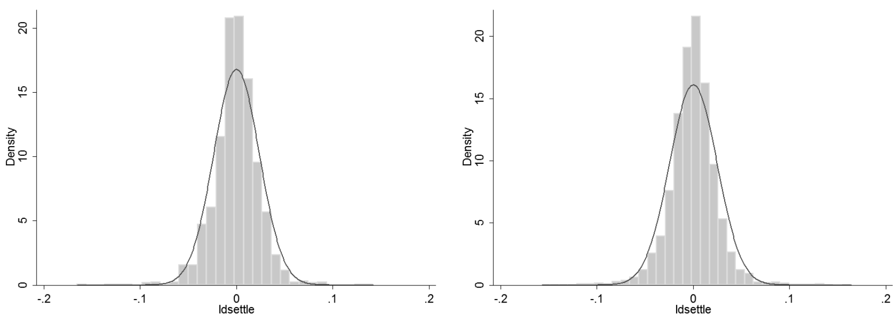

Figure 6.8: **Distribution of crude oil futures returns**

For the first and second period, ARMA (3,2) and ARMA (2,2) respectively were chosen to model the conditional mean. The square residuals are again highly correlated as seen by the ARCH-LM test (the values of TR^2 are respectively 48.481 and 408.612).

Table 6.8: **Crude oil: Assessing the best ARCH model**

σ_t^2	const	α_1	α_2	α_3	LL	AIC
First period						
EGARCH (1,1)	-.338313 (0.000)	.0084226 (0.449)	.2138141 (0.000)	.953672 (0.000)	4087.865	-8155.7
Second period						
TGARCH (1,1)	.0001534 (0.001)	.0806655 (0.000)	-.058655 (0.000)	.953554 (0.000)	8786.921	-17553.84

Source: Author's results

As noted in Table 6.8 the coefficient α_1 on the asymmetric term in the first period is positive but not significant with the p value of 0.449. In the second period the coefficient is negative and significant which again implies the presence of the **leverage effect** and **loss aversion**. Again, the graphical representation of the leverage effect is depicted in Figure 6.9. The power of the asymmetric effect is in both periods smaller than the symmetric one meaning that the symmetric effect dominates the asymmetric one.

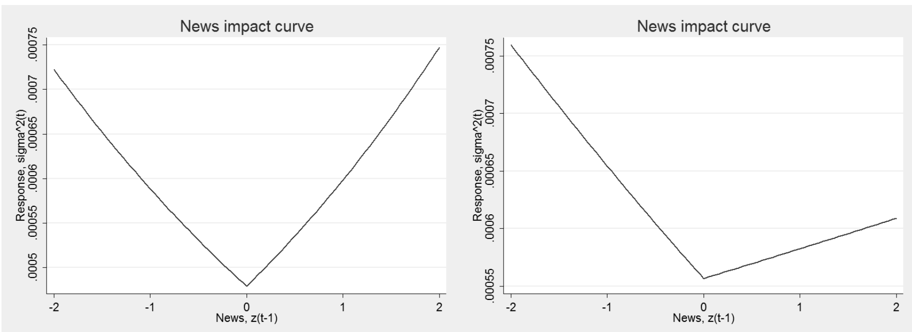

Figure 6.9: **Crude oil: News impact curves in first and second period**

The term α_3 which expresses the volatility persistence is again in both periods very high and significant, which confirms the presence of **volatility clustering** in the data.

Table 6.9: **Crude oil: Assessing the best ARCH model with SI dummy**

σ_t^2	const	α_1	α_2	α_3	$\Delta SI \leq 0$	$\mid \Delta SI \mid$
First period						
EGARCH (1,1)	-.2318085 (0.000)	-.0110724 (0.306)	.1647675 (0.000)	.9673122 (0.000)	10.72009 (0.000)	-1.665012 (0.000)
LL: 4103.929 ; AIC: -8183.858						
Second period						
EGARCH (1,1)	-.0697834 (0.000)	-.0555326 (0.000)	.1131679 (0.000)	.9905568 (0.000)	4.511422 (0.000)	-.3970251 (0.006)
LL 8719.768 ; AIC -17417.54						

Source: Author's results

The parameters on the sentiment index (Table 6.9) are highly significant in both periods. In both periods the increase of SI volatility slightly decreases the volatility of returns but when the change in SI is negative the SI volatility increases cause the increase of volatility of returns. This effect greatly dominates the symmetric one. The estimated effects of a negative change in SI are in accordance with the assumed relationship. The power of the sentiment terms is more than twice larger in the first relatively calm period.

6.4.4 Comparison of the results

First, the comparison of the power of the leverage effect for each contract is provided. Overall, the loss aversion was detected across all periods and contracts except one period of crude oil futures where the leverage effect was positive but nevertheless insignificant. These results confirm the loss aversion in investors decision making since they are more sensitive to bad news (possible losses) which is thereupon reflected in a higher volatility of returns that has consequently an impact on the formation of futures prices.

For all contracts the loss aversion is higher in turmoil periods, which could be associated with a higher risk which the investors had to undertake during these periods. The strongest negative leverage effect is present in S&P 500 futures - those which are referred to be a proxy for the entire U.S. market.

Second, the models in which the SI term is included are compared. In case of cotton the positive changes of SI have a large influence on the volatility of returns but the negative changes do not. This could be explained in a following way. When there are positive news, a lot of investors enter in the futures contracts with the high expectation of a possible gain. Nevertheless in the case of futures the investors will eventually close the position either way because the duration is limited and they are forced to close the position at the end of the duration anyway. Thus the negative change in the SI is guaranteed and in most cases it does not have to be influenced by any bad news in the market. Therefore the SI in the form presented in this research is probably not a good measure of an investor sentiment at the cotton futures market in the period examined.

In case of S&P 500 futures the sentiment index is not significant in either form in the first - relatively tranquil - period and it is significant only in the form of any change in the second - turmoil - period in which the parameter on the term is positive which is the expected effect. Nonetheless we cannot properly analyze the effect for S&P 500 futures as the results are mostly not significant.

On the other hand the assumed relationship is confirmed at 99% confidence interval for crude oil futures contracts. The complete opposite relationship of the parameters compared to cotton futures could be observed because the crude oil market is more competitive and riskier since many political problems, wars and uncertain future project at this market. Therefore investor act of entering into the contract and closing the position depends on the current events more than in the case of cotton market.

In both cases of cotton and crude oil the power of SI terms is larger in the relatively tranquil periods than in the turmoil ones and the power of the other terms is consequently smaller. In the turmoil periods the volatility may be influenced by various other factors which are included in the unexpected news in the form of the lagged residual term and thus it makes the SI less important.

The observations in this analysis were divided in shorter periods according to the results of the QLR test as opposed to the approach of Serrão (2015) - whose research on investors behavior was closely followed in this work - who simply divided the sample into more periods with the same number of observations. Moreover the history of the market was provided to allow the comparison of the results with the evolution of the market.

Chapter 7

Conclusion

Behavioral finance has a promising future application in finance. It develops theories, examples and models that fit the real market behavior in a more accurate way than the Efficient market hypothesis and other theories based on the rational investor. Unfortunately, it does not establish exact relationships which would be applicable uniformly on the entire market as different factors affect different markets which the model cannot account for in a uniform form. For example, there have been attempts to quantify the parameters of PT value and weighting functions (including the degree of an investors loss aversion) as covered in section 4.3 but each researcher who uses a different model and a different sample always arrives to a diverse result than the other one.

According to the author of this thesis the models cannot be ever uniformly quantified to forecast the development of various markets. However we can consider the general characteristics which have been described by behavioral finance and apply them on each market separately and thus forecast the behavior probably more accurately than a model according to the classical theory would.

For the purpose of this research futures contracts on cotton, crude oil and S&P 500 index were chosen for the analysis. Thus we could first study the differences between each market and next attribute the diverse results of the analysis for each contract to the market specifics and make conclusions about the behavior of investors at different markets. The analysis was performed using ARCH type models which allowed to examine an asymmetric leverage effect of daily returns on their volatility.

The procedure followed the approach conducted by Serrão (2015) who considered the asymmetric leverage effect as the proof of a loss aversion of investors. Moreover a measure of an investor sentiment defined in equation 6.15 was incorporated in the model of conditional volatility of returns and its influence on the volatility was examined.

Overall it was showed that the loss aversion and the volatility persistence differ significantly at each market and it probably depends also on other market specifics of the individual contracts which variously change during the observed period. The strongest leverage effect was observed for S&P 500 futures. It was estimated to be more pronounced in periods which were indicated to be more turmoil ones than the others. This feature is assigned to a riskier environment in which people can be more loss averse.

The measure of an investor sentiment as defined in this thesis was significant only for cotton and crude oil contracts. However, the today volatility of cotton futures returns was estimated to be higher when the change of the sentiment index is positive than negative. That is in conflict with the assumption that the negative news should induce higher volatility than good news. This result could be different if it would be recognizable if the investors closed the positions because the maturity month has been reached or because the bad news emerged and they want to let go a nonprofitable investment. Finally other stylized facts about volatility stated in Chapter 2 as fat tails and high peaks of the distribution and volatility clustering were confirmed in all samples.

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