University of St. Gallen

Explaining Futures Returns with Disclosed Trading Positions

Bachelor Thesis

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Abstract

This thesis investigates the relation of publicly disclosed trading positions and returns in the U.S. futures markets. A varied portfolio of ten different futures contracts is analyzed empirically. It is found that hedgers reduce their net positions in periods of rising futures prices and vice versa. In contrary, speculative investors tend to increase their holdings in periods of appreciating futures prices. In the majority of cases, speculative traders were able to obtain a positive price spread, at the expense of hedgers. A test for risk premia showed inconclusive results. Superior market timing abilities were discovered in some of the markets investigated. An investor sentiment index was used for forecasting purposes. Evidence suggests that investor sentiment generally can not be interpreted as a reliable indicator of futures returns in subsequent periods. High sentiment levels of small traders seem to be a fairly reliable contrary indicator, however. A sentiment-based trading strategy failed to outperform other trading strategies and asset classes.

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1 Introduction

1.1 Topic

A key issue in financial markets research is the question whether some market participants succeed in consistently outperforming the market. In this regard, researchers often face the problem of limited data availability. More often than not, representative track records of traders are simply not available to the public. Therefore, this field of research has resorted to asset classes where this problem does not apply. Mutual funds, for instance, often feel impelled to publish their performance records in order to attract new investors. Consequently, there is already extensive literature[1] on the persistence of mutual funds performance

U.S. futures markets are another example of an asset class for which trading positions data is available for research. Contrary to the mutual funds market, trading data in futures markets is only available on an aggregate basis. This information is provided by the U.S. Commodity Futures Trading Commission (CFTC) in form of the Commitments of Traders (COT) reports which are published on a regular basis. The advantage of using this dataset for research is that it covers all futures traders on the U.S. market rather than a less representative sub-sample. Overall, academic literature on the COT data is still scarce, however. Considering that the regularly released COT reports are closely monitored by market practitioners, this is rather surprising. By combining trading position data with according time series of futures prices, one can obtain valuable insights on market mechanisms that are relevant to academic research as well. For instance, return forecasting abilities, risk premia and price formation mechanisms are fields of research which could benefit from the availability of these datasets. This thesis will pick up some of these topics and will link them to empirical results.

1.2 Literature review

The literature review outlines the state of the art in research fields relevant for this thesis. In particular, the findings of academic research with regards to the relation between trading positions and futures returns are presented. For the numerous studies reported here, a distinction can be drawn concerning the underlying data. Similar to this thesis, many empirical studies are based on trading positions disclosed in the publicly available Commitments of Traders reports. Other studies, in contrary, work with non-public datasets. While the Commitments of Traders reports only include aggregate trading positions, some of the authors had access to detailed trading records of individual traders. Common sources for such disaggregated data are large broker houses that made their client's records available for research and the Commodity Futures Trading Commission which has also provided some

[1] See for example Brown & Goetzmann (1995) and Carhart (1997).

researchers with datasets that are more detailed than the publicly available Commitments of Traders reports. In a very comprehensive study, Stewart (1949) laid the foundations for the empirical research of traders' performances in futures markets. He analyzed the trading records of more than 9,000 individual clients of a brokerage firm. The study evaluated the performance of these small traders in the wheat, corn, oats and rye futures markets from 1924 to 1932. Stewart's most striking finding was that about 75% of the traders lost money on the futures markets while only the remaining quarter had a positive return. He discovered a "clear tendency of small traders to cut their profits and let their losses run". Taking into account that futures markets are a zero sum game where profits and losses must balance, he reasoned that "there must be other groups - large speculators, scalpers, spreaders or hedgers - which make very large profits". In a more recent study, Babcock (1989) even reported that between 75% and 90% of traders in futures markets exhibited negative performances.

Houthakker (1957) was among the first to work with Commitments of Traders data in order to find out about forecasting abilities of speculators. In his study he examined the aggregate trading results of large hedgers, large speculators and small traders in the corn, wheat and cotton futures markets. The examined period was 1937 to 1952. By linking changes in aggregate trading positions to moves in futures prices, Houthakker discovered that in all of the three markets analyzed, large hedgers lost and large speculators gained, on aggregate. The results for small traders were mixed. Therefore, he concluded that "hedgers [...] are the mainspring of profits for the other traders". The outperformance of large traders as compared to small traders was attributed to superior forecasting skills.

Chang (1985) criticized earlier studies with regards to their assumption that returns to speculators in futures market are normally distributed. His criticism also targeted the fact that some earlier studies like Houthakker (1957) did not include any statistical significance tests. Consequently, he made use of the Henriksson & Merton (1981) non-parametric test (HM) to examine traders' market timing abilities in the wheat, corn and soybeans market. The HM test goes without the assumption of normally distributed returns. Instead, it compares the number of "correct" trading decisions with the number of "incorrect" trading decisions to evaluate forecasting skills. A trading decision is "correct" if a trader's net position[2] is followed by an increase in the corresponding futures price and vice versa. The study was based on COT data in the period from 1951 to 1972. Chang was able to reject the null hypothesis that speculators do not earn positive returns in all markets investigated. Furthermore, it was found that large hedgers were consistent losers. The study also examined the type of returns speculators received for their market activities. In more detail, Chang distinguished between rewards for assuming risk (risk premia) and rewards for market timing abilities (forecasting abilities). Interestingly, the study showed that only the speculators in the wheat market had significant timing abilities. Therefore, speculators' positive returns in the corn and the soybeans market were attributed to risk premia.

[2] The net position of a trader is calculated by subtracting the amount of short contracts held in a specific futures market from the respective amount of long contracts.

The overall positive returns to speculators and negative returns to hedgers were interpreted as strong support to Keynes' (1930) theory of normal backwardation.

Two years after Chang's study was published, Hartzmark (1987) reported completely contradicting results: He concluded that "commercial (hedging) traders are most profitable, while noncommercial (speculative) traders earn negative or zero profits". Hartzmark rejected the theory of normal backwardation, as he could not find any rewards to speculators. For his study, Hartzmark used a 4½ years sample (1977-1981) of confidential CFTC files that included the daily positions of large speculators and large hedgers. In total, track records of 4,567 individual traders in 9 different futures markets were part of the dataset. Another important finding was that a small minority of hedgers earned the better part of all profits. Interestingly, Hartzmark found that 0.1% of the hedgers earned 58% of the total net profits. How can these differences to Chang's results be explained? It was Chang (1985) himself to concede that his results should be interpreted with great caution: Chang only analyzed whether the trader groups on average were positioned "right" more often than "wrong". Two caveats are noteworthy: First, Chang reported only aggregate results. He explained the problems with regards to the limited explanatory power as follows: "Large speculators as a whole may have made either positive or negative profits in the market, but the profitability of individual large speculators has not been explained and may not be consistent with our findings." Second, Chang's article did only investigate the amount of "right" and "wrong" positions. However, it did not study the extent of the gains and losses. If, for example, speculators earned a minor average amount for their correct trading positions and lost a significantly higher amount, on average, for their incorrect trading positions, they still would have incurred a loss in total, despite being "right" more often than "wrong". The case of Chang's and Hartzmark's studies clearly reveals the problems related with aggregate data sets. When working with aggregated Commitments of Traders data, however, researchers are limited to testing methods that are suitable for these kinds of datasets like, for instance, the HM market timing test and similar procedures. Detailed studies on the aggregation level of individual traders call for trading records that are not available to the public.

Using the same disaggregated set of trading data in another study, Hartzmark (1991) examined the forecasting abilities of traders in seven agricultural and two financial futures markets. Again, the sample period was 1977 to 1981. Hartzmark concluded that the returns futures traders reported were randomly generated and could not be attributed to forecasting skills. Furthermore, the results showed that traders who did exceptionally well in the first half of the sample period generally failed to perform above average in the second half. On the other hand, traders who underperformed in the first half tended to improve in the second half. Consistent with Hartzmark (1987) it was found, however, that hedgers used to have slightly better forecasting abilities than their speculator counterparts. In addition, hedging traders also seemed to perform better at forecasting strong price fluctuations. Nevertheless, most of the study's results were not statistically significant.

The study by Leuthold, Garcia, & Lu (1994) was closely linked to Hartzmark's research. Leuthold et al. explored the frozen pork bellies market - a market already analyzed by Hartzmark

(1991) in more detail. The data used were end-of-day commitments of large reporting traders from 1982 to 1990. In total, the sample comprised of 3,171 traders with records of over 450,000 trades. In this study, traders have not been categorized (e.g. hedgers or speculators). The study only included reporting traders, however. Due to the CFTC's reporting rules, it can be reasoned that the sample must have consisted of large hedgers and of large speculators, while small nonreporting traders were not included in the sample. Leuthold et al. reported significant profits for all traders analyzed. As total gains must equal total losses in futures markets, the out-of-sample players, namely the small nonreportable traders, must have lost. In this sense, these findings were similar to the results of Stewart (1949).

In 2001, Buchananan et al. claimed to provide "a method of predicting the direction of spot price movements in the natural gas market". In fact, however, their study addressed exactly the same issues already known from Hartzmark (1991) and Leuthold et al. (1994). Using the Cumby and Modest (1987) extension of the HM market timing model, Buchananan et al. (2001) discovered that "large hedgers appear to be significant losers" while "large speculators appear to be consistently able to forecast the direction of price movements". Moreover, it was found that large speculators successfully took their largest positions prior to major price changes.

With his 2001 paper, Wang opened a completely new field of research: His empirical study presented initial evidence on how future commodity prices can be inferred from disclosed trading positions. Wang constructed an investor sentiment index that set traders' current net positions into relation to their past net positions. He then performed a series of regressions on futures prices in six agricultural futures markets. Among his findings were that large speculator sentiment could be considered to be a price-continuation indicator, while large hedger sentiment, on the other hand, could be interpreted as a contrary indicator. Small trader sentiment has turned out not be useful for forecasting purposes. The market timing strategies presented have shown that extremely low and extremely high investor sentiments proved to be quite reliable indicators for futures prices forecasting. Contrary to Chang (1985), Wang (2001) did not find any evidence of superior forecasting skills of speculators. In a more recent study, Wang (2003) applied the same methodology to the market data of the S&P 500 futures contract. There, the results were exactly the same: "It is found that speculator sentiment is a price continuation indicator. In contrast, hedger sentiment is a contrary indicator. Small trader sentiment is hardly useful for forecasting".

1.3 Research questions and scientific contribution

As shown by the literature review, previous research focused on analyzing the flows of money between the types of traders. The main research question was "Who wins and why?". So far, there is hardly any literature that explicitly takes the perspective of interpreting trading positions at present time in order to gain information on likely future price movements from an *ex-ante basis*. Instead, most of the literature in this field of research concentrated on investigating the existence of risk premia and on analyzing forecasting abilities of market participants, performing an *ex-post analysis*. Exceptions are the papers by Wang (2001, 2003). In this thesis Wang's results will be taken up and will be broadened and deepened by additional empirical tests. In doing so, this thesis shall in several ways extend the yet scarce knowledge about how current trading positions can be interpreted in order to obtain indications for futures contracts' performance in subsequent periods. In this new field of research, there is plenty of room for scientific contribution. Wang (2001) reported that disclosed trading positions proved to be useful for forecasting futures prices in agricultural markets. One important research question that will be answered is therefore, if this phenomenon is limited to agricultural futures contracts or if it applies to futures markets in general. In order to answer this question, a wide variety of futures contracts will be analyzed. Accordingly, this thesis will present initial empirical results on seven futures contracts that have not yet been researched in this regard.

A question that is of interest especially for practitioners is how the findings presented in Wang's papers and in this thesis can be implemented in practice. Wang (2001) already gave some basic hints for implementing a trading strategy. Consequently, an important goal of this thesis is to extend this knowledge. A whole chapter of this thesis is exclusively dedicated to this issue. In particular, that part of the thesis will examine the feasibility and performance of a futures trading strategy based on reported trading positions. Obviously, only reporting the empirically obtained links between trading positions and futures returns is not is not sufficient. Such findings have to be backed by economic reasons. Therefore, the parts of this thesis that investigate the performance of trader groups and the components of trading returns act as the vital link to economic theory.

Due to the fact that there is only contradictory literature on this topic, analyzing the flows of money between groups of traders will be an integral part of this thesis. The results of this part will be used as a basis for the empirical forecasting analyses. The literature review has shown that several research papers have already studied the trading records of the different types of traders. The question "who wins and why" has still not yet been answered satisfactorily, however. In some cases, scholars even reported diametrically opposed results. There are three obvious explanations for these contrarian results: First, the researchers may have studied different markets. Second, different sample periods may have been subject of their studies. Finally, different methodologies may also have contributed to differing outcomes. Consequently, an important scientific contribution of this thesis is that it explores a wide portfolio of futures contracts during the same period with a consistent methodology. This way, some evidence on whether these contradicting findings may have been the result of different methodologies and time periods or, if real differences with regards to the performance of futures traders exist across futures markets, is obtained.

1.4 Structure of the thesis

The remaining parts of this thesis are structured as follows: Chapter 2 is devoted to studying the types of traders and their behavior in futures markets. First, the portfolio of analyzed futures markets will be presented together with descriptive statistics. Then, section 2.2 will explain the role of the different types of traders and their motives for engaging in the market. Subsequently, the Commitments of Traders report, which is the data source of trading positions for further analyses, is presented in full detail, followed by a regression analysis that investigates the relation between futures returns and trading positions. In order to assess the impact of trading positions, the performances of the major types of traders will be investigated. By means of theoretical and empirical arguments, the two subsequent sections will explain the relation between futures returns and trading positions. In particular, the role of risk premia and forecasting abilities of traders will be examined.

Based on the findings from the precedent sections, chapter 3 will introduce a sentiment index that sets contemporary trading positions in relation their historical extremes. This way, an oscillator index will be generated. A regression model will analyze the usefulness of the sentiment index for market timing decisions.

Chapter 4 assumes the perspective of a practitioner who intends to use the findings from previous parts of the thesis in order to implement a trading strategy. Following the description of the trading strategy, the performance of trading signals will be studied. Then, a sensitivity analysis will test the robustness of the results. Finally, the performance of the trading strategy will be compared to the outcomes of a buy and hold strategy and to the returns of other asset classes. The thesis will conclude with a summary of the most important findings.

2 Futures traders and their market behavior

2.1 Analyzed futures markets

Ten selected futures markets will serve as the basis for all of the empirical studies presented in this thesis. As already outlined, the main research question is to find out whether disclosed trading positions in general are useful to predict returns in subsequent periods. Wang (2001, 2003) concluded that disclosed trading positions indeed seem to be suitable for explaining some of the variance in futures prices. However, the explanatory power of his papers is limited because they only analyzed agricultural futures and the S&P 500 future. In particular, the agricultural futures markets dropped heavily as a percentage of overall trading volume (Leuthold, Junkus, & Cordier, 1989). Due to the declining importance of these markets, it would be grossly negligent to make any generalizations without further empirical evidence. In order to find out whether the findings by Wang apply to all major types of futures contracts, a portfolio that consists of ten futures contracts has been constructed. The portfolio should work as an approximation to the futures market in general. Therefore, contracts from all major categories of futures have been included.

Table 1: Analyzed futures contracts

Category	Futures contract	Shortcut	Contract size	Exchange
Agriculturals	Corn	Corn	5,000 bushels	CBOT
	Wheat	Wheat	5,000 bushels	CBOT
Energy	Light Sweet Crude Oil	Oil	1,000 barrels	NYMEX
Equity	S&P 500	SP500	$250 times S&P 500 Index	CME
Foreign Exchange	Japanese Yen	JPY	12,500,000 Japanese Yen	CME
	Swiss Franc	CHF	125,000 Swiss Francs	CME
Interest Rates	30 Year U.S. Treasury Bond	Bond	$100,000 face value	CBOT
	2 Year U.S. Treasury Note	Note	$200,000 face value	CBOT
Precious Metals	Gold	Gold	100 troy ounces	NYMEX
	Silver	Silver	5,000 troy ounces	NYMEX

Sources of futures contracts specifications: CBOT, NYMEX and CME websites. Shortcut descriptions of futures contracts as denoted here will be used in all further tables in order to conserve space.

Table 1 displays the ten selected contracts. The portfolio consists of contracts from the agriculturals, energy, equities, foreign exchange, interest rates and precious metals categories. As another diversification argument, great importance has also been attached to the fact that the selected contracts are traded at different U.S. futures exchanges. Corn and Wheat have been chosen as a proxy to the agricultural futures market. They belong to the world's most important grains, as measured by trading volume. Light Sweet Crude Oil, traded at the NYMEX, is the most important oil futures contract and has been selected to represent the class of energy futures. The Japanese Yen and the Swiss Franc contracts stand for the foreign exchange futures market. Euro-related contracts could not been considered because the sample of this thesis is 15 years, namely from the beginning of 1992 to the end of 2006, while the Euro was not introduced as legal tender before 2002., The 30 Year U.S. Treasury Bond future has been added to the portfolio as it is one of the world's most heavily traded contracts. The 2 Year U.S. Treasury Note has been included to represent interest rate instruments with lower maturities. Finally, Gold and Silver are the two precious metals contracts in the portfolio. Table 1 also includes a column with shortcuts. These abbreviated labels of the futures contracts will be used in all further tables in order to conserve space.

Historical futures prices have been obtained from Datastream. In this regard, a practical problem is the fact that single futures contracts typically have maturities of only some months, while the observation period of this thesis is 15 years. Therefore, the futures price series have to be constructed by stringing together the prices of consecutive individual futures contracts. The Datastream documentation explains how continuous series are put together: "The continuous series is a perpetual series of futures prices. [...] It starts at the nearest contract month which forms the first values for the continuous series until the first business day of the actual contract month, or until the contract reaches its expiry date, whichever comes first. At this point the next trading contract month is taken." Compared to asset classes without fixed maturities like equities, for instance, the need for such a provisional arrangement is a disadvantage, of course. A visual analysis of the price graphs has shown that the price jumps during the transitional period from the expiring futures contract to the next is negligible, however.

Table 2: Descriptive statistics of the price time series

	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Number of observat.	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913
Mean	247.35	342.90	28.56	940.81	0.89	0.72	100.00	102.14	363.73	559.65
Median	232.75	335.75	22.39	1024.20	0.88	0.71	99.98	101.86	354.00	509.50
Maximum	516.25	716.50	77.03	1555.40	1.25	0.90	122.66	108.62	721.50	1487.90
Minimum	174.75	230.75	10.72	395.25	0.68	0.55	79.93	96.38	252.80	352.50
Annualized st. dev.	50.81	69.03	14.97	344.39	0.09	0.08	9.65	2.73	83.72	187.49
Skewness	2.03	1.00	1.51	-0.24	0.80	0.02	-0.03	0.54	1.53	2.49
Kurtosis	8.39	4.27	4.34	1.67	4.65	2.08	2.04	2.46	5.81	9.48

Sample: 01/01/1992-12/31/2006. Data source: Datastream.

Table 3: Descriptive statistics of the return time series

	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Number of observations	3,912	3,912	3,912	3,912	3,912	3,912	3,912	3,912	3,912	3,912
Mean daily return	0.01%	0.01%	0.03%	0.03%	0.00%	0.00%	0.01%	0.00%	0.01%	0.03%
Annualized mean return	2.91%	1.42%	7.72%	8.16%	0.40%	0.82%	1.63%	0.03%	3.87%	7.93%
Median daily return	0.00%	0.00%	0.00%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Maximum daily return	9.80%	8.88%	14.23%	5.75%	8.27%	3.93%	2.13%	0.65%	8.89%	9.29%
Minimum daily return	-21.65%	-15..93%	-16.54%	-7.76%	-4.21%	-3.99%	-2.98%	-1.03%	-7.57%	-14.79%
Annualized st. dev.	23.69%	25.94%	34.27%	16.58%	11.54%	11.47%	9.14%	2.09%	14.16%	25.49%
Skewness of daily returns	-0.2848	0.1232	-0.2637	-0.1306	0.8325	0.0966	-0.4011	-0.9795	0.1275	-0.7402
Kurtosis of daily returns	18.5091	8.1228	7.0580	7.9775	11.8450	4.9507	4.5583	11.0782	12.6758	11.1079
Jarque-Bera statistic	39259	4288	2730	4050	13204	626	501	11262	15271	11073
Prob. of normal distr.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Sample: 01/01/1992-12/31/2006. Data source: Datastream.

Descriptive statistics of the continuous price series are displayed in Table 2. The sample period of 15 years included 3,913 trading days. Thus, a year in the sample period comprised of 261 trading days on average. Table 2 also shows some additional distribution parameters. The descriptive statistics of the daily return[3] series are displayed in Table 3. In the overall sample period, all futures contracts have yielded positive returns. However, the extent of annualized mean returns differs strongly. From 1992 to 2006, the Oil, the Silver and the S&P 500 future appreciated the most, namely by roughly 8% per year on average. On the other hand, the prices of the two foreign exchange futures and the U.S. Treasury Note future remained rather stable. In 6 markets the returns were negatively skewed and in 4 markets they were positively skewed. The Jarque-Bera (1980, 1981) statistic clearly rejects the null hypothesis of normally distributed returns.

2.2 Types of traders

The economic reasoning for the existence of futures markets is that they allow for hedging against price fluctuations. Traditionally, futures markets were used by producers and consumers of commodities like agricultural products, metals and sources of energy. Consider the classic example of a wheat farmer whose only source of income are the sales revenues from his annual harvest. Without engaging in the market for wheat futures, the revenues from selling his harvest would be dependent on the price of wheat at harvest time, and thus would be highly insecure. Nevertheless, the farmer has to decide several months in advance whether to grow wheat or other grains or whether to completely withdraw from business if prices are considered unfavorable. By entering a short position in wheat futures, however, the farmer can lock in his expected revenues at the current futures price. Let us assume that the cash price of wheat at the end of the harvest season turns out to be lower than the cur-

[3] Daily returns are calculated as $\ln\left(\frac{p_t^j}{p_{t-1}^j}\right)$ where j represents the futures contract.

rent spot price. In this situation, the farmer would incur cuts in his wheat's sales revenues. However, these losses would - according to hedging theory - be offset by the gains from his short position in the futures market. Therefore, short hedging is used by holders of inventories to determine revenues in advance (Cootner, 1960). Knowing the amount of revenues in advance, the farmer can fully concentrate on his core business and can plan his production and investments accordingly. Most importantly, by observing the futures prices, a producer knows if the selling price of his product will be above or below his production costs even before he has to make his business decisions. On the other side of the market, consumers of commodities use futures markets for similar reasons: While the farmer used wheat futures contracts to lock in expected revenues, a flour mill would use the same contracts to lock in expected costs of its main input good, namely wheat. The advantages of improved financial planning apply here as well. Examples for hedgers are raw material producers, processors and users, financial intermediaries and international trading firms (Leuthold et al., 1989).

In the above example it was implicitly assumed that futures are suitable for hedging against price fluctuations. That is, changes in the spot price should equal changes in the futures price. Testing the effectiveness of hedging has been the subject of several empirical studies. Working (1953) provides an early overview. It is uncontested that changes in futures prices roughly equal changes in spot prices. However, the studies found that the relation is far from perfect (Working, 1953). Therefore, hedging with futures contracts reduces price risk strongly but fails to completely eliminate it.

For about a century, agricultural products have been the only underlying of futures contracts. At that time, the futures market's sole purpose at that time was to encounter price risk in agricultural commodities. Then, the Chicago Mercantile Exchange (CME) took a pioneering role in introducing the world's first financial futures, namely seven contracts on foreign currencies (Chicago Mercantile Exchange, 2007). In 1977, the Chicago Board of Trade (CBOT) enlarged its product portfolio by launching the U.S. Treasury Bond contract, which in its 10 year version today is the world's most actively traded futures contract (Chicago Board of Trade, 2007). Nowadays futures on financial instruments are by far futures exchanges' most important securities (ibid.). Besides futures on U.S. Treasury Bonds and foreign currencies, contracts on major equity indices like the S&P 500 are available. The introduction of these new futures contracts was a reaction to changing macroeconomic conditions: When formerly fixed foreign exchange rates were allowed to fluctuate as a consequence of the collapse of the Bretton Woods system, businesses were facing a new kind of risk (Leuthold et al., 1989): Exchange rate risk. With futures contracts on foreign exchange, business executives of companies with international operations were given a means to effectively hedge exchange rate risk. For interest rate futures, the development was very similar: Fluctuating interest rates turned out to be another source of business uncertainty. Consequently, the introduction of the U.S. Treasury bond contract was the equivalent tool to tackle these issues.

Apart from reducing business risks, hedging has the important economic effect of "promoting the stockpiling of commodities in private hands in times of surplus, inducing the economical storage of such stocks, and prompting their release for consumption at appropriate times" (Working, 1953). In this context, the carrying charge - as expressed by the difference in futures prices for different maturities - works as the incentive to store the commodities. Obviously, the higher the carrying charge in a futures market, the more market participants will decide to store the commodity.

A futures market consisting only of hedgers would never be able to work effectively. In futures markets, the number of short positions must always equal the number of long positions because each contract requires a party and a counterparty that assume opposite positions. In reality, however, it is very unlikely, that the aggregated hedgers' demand for short positions will equal their demand for long positions. This is where another type of trader, the speculative investor, comes into play. Speculative investors enter the market for completely different reasons, as compared to hedgers. In general, they do not have any business-related connections to the traded commodity and they do not engage in futures markets to hedge against risks. Instead, speculative investors regard the futures market as another asset class to invest their capital[4]. Typical speculators are commodity trading advisors (CTAs), commodity pool operators (CPOs), or floor brokers (Sanders, Boris, & Manfredo, 2004). Their motive is to benefit from price movements in futures contracts by taking positions they consider to be favorable. Positioning decisions are based on the information available to speculative investors and on the way they interpret it. Leuthold et al. (1989) explain very accurately: "[Speculative investors] must judge that the market is in error or that prices are too high or too low". Other than hedgers, speculative investors are in the comfortable situation of being able to decide if and at what times they want have market exposure. Usually, speculative investors only take positions in a market if they believe that market prices do not correctly reflect the value of the futures or if they have private information that the market does not seem to be taking into account. In contrary, hedgers generally do not have this range of options. Their courses of business force them to take corresponding positions in the futures markets. Therefore, the existence of speculating activity is indispensable for well-functioning futures markets. Speculative investors increase the liquidity of the markets and can take counter positions in cases of hedgers' demand surplus for long or short positions. In today's futures markets, speculative investors account for positions that sum up to a considerable portion of the open interest, as will be shown later.

In its publications, the CFTC uses an alternative terminology to label the types of market participants which will also be adopted in the remainder of this thesis. The CFTC differentiates between three types of traders:

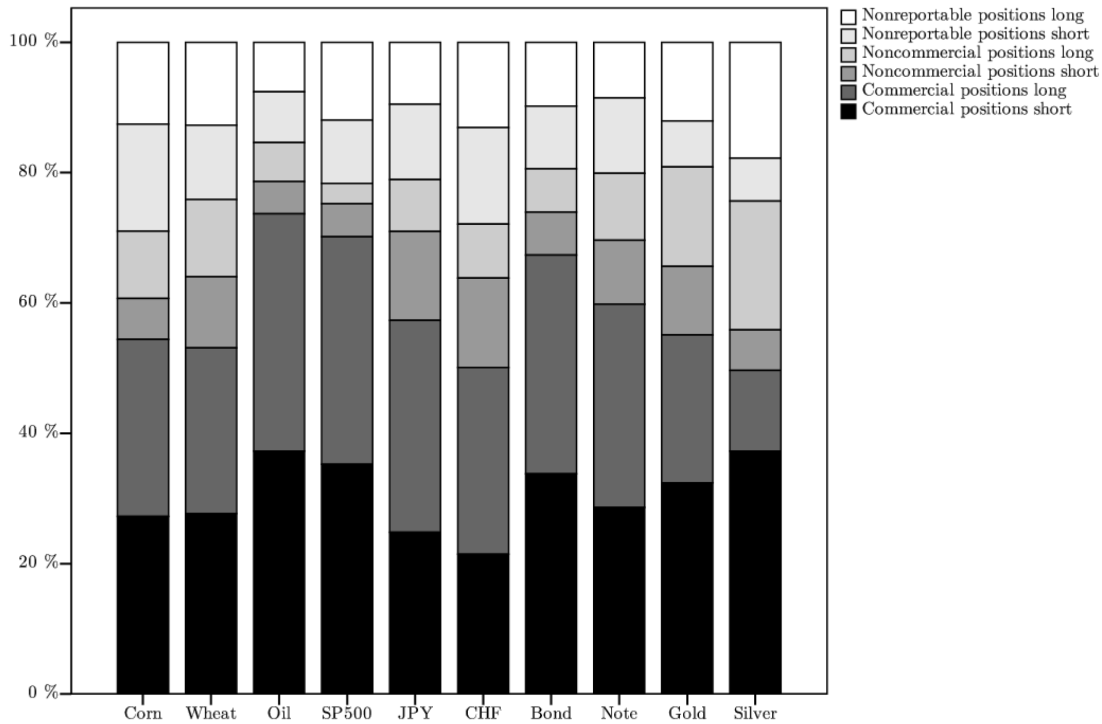
- **Commercial traders (Commercials)** are "trading entities that are engaged in business activities hedged by the use of the futures or option markets" (Commodity Futures Trading Commission, 2007). Therefore, the classic attributes of a hedger, as described above, apply to this type of trader.

[4] It shall be noted that, apart from margin accounts, trading in futures markets does not require any capital. Therefore, investing in this regard does not mean that capital is provided. Instead, risk is taken.

- **Noncommercial traders (Noncommercials)** are market participants who are *not* "engaged in business activities hedged by the use of the futures or option markets" (Commodity Futures Trading Commission, 2007). As they do not have any business risk that they would hedge, they are altogether subsumed under the speculative category.
- For the third category, the **nonreportable traders (Nonreportables)**, there is no clear-cut definition of their motives for futures trading. Theoretically, they could be either hedgers or speculative investors. The only unifying element of nonreportable traders is the fact that their individual positions are too small to be subject to report. It is commonly assumed that Nonreportables are predominantly speculative in nature. See for example Houthakker (1957) and Chang (1985).

Every futures market participant falls in one of these categories as the three types of traders as defined by the CFTC are mutually exclusive and collectively exhaustive. Only Commercials and Noncommercials are required to report their open positions to the CFTC, not so the Nonreportables (Commodity Futures Trading Commission, 2007).

Figure 1: Mean size of trading positions



Sample: 01/01/1992-12/31/2006. Data source: CFTC COT reports. Reported values are percentages of double the open interest, excluding spreading positions.

Figure 1 shows the size average sizes of the long and short positions of the three types of traders, as defined by the CFTC. Reported values are average percentages of two times[5] the open interest in the respective markets, from the beginning of 1992 to the end of 2006. Historical averages were calculated from the trading positions reported in the CFTC's COT reports. The characteristics of the COT report will be covered in more detail in the following section.

Commercial traders seem to be the largest group of traders, regardless of the market investigated. Except for the silver market, commercials accounted for over 50% of the double open interest. This suggests that hedging operations are still the main driver of futures market liquidity. Albeit being small individually, Nonreportable traders' positions sum up to considerable amounts. In most of the markets, their positions even exceed those of the large speculators. Commercial positions are strong especially in the Light Sweet Crude Oil, the S&P 500 and the U.S. Treasury Bond markets. The data suggest that these contracts have been used primarily for hedging purposes. As opposed to this, Noncommercial positions account for only 8% in the S&P 500 market and 11% in the Light Sweet Crude Oil market. According to the data, Corn and Swiss Franc contracts seem to be very popular among small speculators. For this analysis, the Silver market is of special interest. There, Commercial short positions exceed Commercial long positions by 25%. This clearly indicates that Silver futures are used extensively for short hedging: Producers of silver engage in short positions to hedge against declining price levels. On the other hand, large and small speculative traders have mostly been betting on rising Silver prices. The situation in the Gold futures market is quite similar. There, Commercial short positions exceed long positions by 10%. In the two foreign exchange futures markets analyzed, in turn, Commercials have been net long. In foreign exchange hedging, "a firm that would lose money in its business operations because of a currency appreciation would take a long position. The business loss from the currency's rise would then be offset by profits from having a long position in the futures market" (Klitgaard & Weir, 2004).

Table 4: Correlation matrix of trading positions

	Commercials' net pos.	Noncommercials' net pos.	Nonreportables' net pos.
Commercials' net pos.	1.0000		
Noncommercials' net pos.	-0.8735	1.0000	
Nonreportables' net pos.	-0.6570	0.2847	1.0000

Sample: 01/01/1992-12/31/2006. Data source: CFTC COT reports.

In order to find out more about how trading positions are related, a correlation matrix has been calculated. Table 4 shows the correlation coefficients of the net trading positions of the three types of traders from the beginning of 1992 to the end of 2006. Again, the data sources are the COT reports published by the CFTC. Because of space restrictions, correlation matrices are not shown for each of the ten contracts analyzed. Instead, only the averages for all ten markets are reported. Unsur-

[5] For calculating the open interest either long or short positions must be summed up. Obviously, the sum of both, long and short positions, must equal two timest he open interest.

prisingly, increases in the net position of the commercial traders are offset by decreasing speculative net positions. The least obvious finding is the correlation coefficient of Noncommercial and Nonreportable traders. Its positive algebraic sign indicates that their net positions generally tend to move in the same direction. That is, large and small speculators seem to increase and decrease their positions at more or less the same time. This finding supports the general notion found in the literature that nonreportable traders are, on average, speculative in nature [Houthakker (1957) and Chang (1985)]. The positive correlation coefficient also makes sense considering the fact that Noncommercial and Nonreportable traders have similar motives for engaging in the market (ibid.). However, it can not be inferred from this data whether or not large speculators have private information that is not available to small speculators and vice versa. It can only be noted that the movements of the net positions of these two trader groups have some commonality. Nevertheless, the low coefficient indicates that there is only a loose correlation, on average.

2.3 Commitments of Traders report

The U.S. Commodity Futures Trading Commission (CFTC) is a public authority appointed by the U.S. Government. Its mission is "to protect market users and the public from fraud, manipulation, and abusive practices related to the sale of commodity and financial futures and options, and to foster open, competitive, and financially sound futures and options markets" (Commodity Futures Trading Commission, 2007). One of the CFTC's most important tools to achieve these goals is the Commitments of Traders (COT) Report which is published by the authority on a regular basis. This report provides the public with up-to-date futures market data. Every futures trader whose positions in the futures markets exceed the reporting level set by the CFTC is legally obligated to report his long and short positions to the CFTC. The traders' declarations then are processed, aggregated and published in the COT reports. In improving the transparency of the markets, the CFTC aims to reduce the risk of market manipulation. However, not all futures markets are covered by the COT reports. Only markets "in which 20 or more traders hold positions equal to or above reporting levels established by the CFTC" are included in the report (Commodity Futures Trading Commission, 2007). Thus, exotic futures markets with low liquidity are generally excluded from the reports. Reporting levels are adapted from time to time and differ among futures contracts. For example, the COT report for the Chicago Board of Trade (CBOT) as of May, 29, 2007 covered 17 futures markets which suggests that only for these contracts reporting levels have been exceeded by at least 20 traders.

The COT reports and their predecessors already exist since 1924 (Commodity Futures Trading Commission, 2007). Since that time, the report has been improved in various ways. First, the publication interval has been reduced. Beginning in 1962, the COT data was published once per month (Commodity Futures Trading Commission, 2007). As of 1990, the publication interval was increased to two times a month, followed by every two weeks in 1992. Later, the CFTC began publishing the COT report even once a week. The sample period for all empirical analyses presented this thesis is

1992 to 2006. Therefore, all statistical evaluations base on bi-weekly and weekly reports, respectively. In total, the trading positions time series using in the empirical part have been compiled from 763 COT reports[6]. Second, the COT report has been released more quickly after the data has been collected. While in 1990 six business days elapsed between the collection and publication of data, the report now is delayed by only three business days. Nowadays, the COT is published each Friday. It contains the trading positions of the preceding Tuesday. When filing their reports on Tuesdays, traders are required to self-identify as Commercial or Noncommercial (Sanders, Boris & Manfredo, 2004). As a further improvement, the reports are made available online by publishing them on the CFTC's website. Finally, the information content of the reports has been expanded. In the 1970s, concentration ratios have been added, as of 1995, the report also included information on option positions and as of 2007 the "Supplemental report" was introduced. In this additional report, the positions of index traders are summarized.

Figure 2: Excerpt from a COT report

WHEAT -- CHICAGO BOARD OF TRADE FUTURES-ONLY POSITIONS AS OF 12/12/06								
NONCOMMERCIAL			COMMERCIAL		TOTAL		NONREPORTABLE POSITIONS	
LONG	SHORT	SPREADS	LONG	SHORT	LONG	SHORT	LONG	SHORT
(CONTRACTS OF 5,000 BUSHELS)			OPEN INTEREST: 417,081					
COMMITMENTS								
73,598	56,045	69,448	237,539	232,901	380,585	358,394	36,496	58,687
CHANGES FROM 05/25/2004			CHANGE IN OPEN INTEREST: -7,043					
-10,463	-1,186	126	3,462	-6,610	-6,875	-7,670	-168	627
PERCENT OF OPEN INTEREST FOR EACH CATEGORY OF TRADERS								
17.6	13.4	16.7	57.0	55.8	91.2	85.9	8.8	14.1
NUMBER OF TRADERS IN EACH CATEGORY (TOTAL TRADERS: 317)								
102	89	92	67	96	233	226		

Source: Commodity Futures Trading Commission (2007).

Figure 2 is an excerpt from a COT report taken from the CFTC website. It shows the Commitments of Traders information for the wheat futures contract as of December 12, 2006. For the analyses performed in this thesis, only net long and short positions of the 3 types of traders are relevant. In the example report it can be seen that commercial traders in total held 237,539 long and 232,901 short contracts, which results in a net position of 4,638 long contracts. Noncommercial traders held 73,598 long and 56,045 short contracts, thus resulting in a net position of 17,553 long contracts. For noncommercial traders, the number of spreading contracts is indicated as well. This figure

[6] This figure may be differ slightly depending on the contract and on the performed analysis.

measures “the extent to which each noncommercial trader holds equal long and short futures positions” (Commodity Futures Trading Commission, 2007). If a noncommercial trader holds, say 10 long contracts and 12 short contracts, 2 contracts will appear in the “short” category and 10 contracts will appear in the “spreading” category. A typical use of spreading positions is to bet on or to hedge against changing price relations of the same futures contract with different maturities. For traders, spreading positions are especially attractive due to the low margin requirements for this trading strategy. The spreading data will not be used in the course of this thesis and has just been explained for the reason of completeness. Finally, the COT reports also contain aggregate data for nonreporting traders. Other than the data for commercial and noncommercial traders, this data is not obtained from traders’ declarations of their long and short positions. Instead, the data for nonreportable traders is simply a residual value. The relationship between the categories of the COT report can be described as

$$L_{Comm} + S_{Comm} + L_{Noncomm} + S_{Noncomm} + 2SPR_{Noncomm} + L_{Nonrep} + S_{Nonrep} = 2OI \qquad (1)$$

where L_i and S_i are the long and short positions of trader type i, $SPR_{Noncomm}$ is the amount of noncommercial spreading contracts and OI is the total open interest (Sanders, Boris & Manfredo, 2004). With the open interest and the positions of commercial and noncommercial traders at hand, the calculation of Nonreportables’ positions is straightforward.

It shall be mentioned that the specifications of the S&P 500 contract have been altered in the mid of the sample period of this thesis. In 1997, the contract size has been changed from \$500 times the S&P 500 Index to \$250 times the S&P 500 Index. In order to ensure the continuity of the time series, the trading positions during the old contract specifications have been multiplied by 2. Contract specification for grains contracts have also been changed during the sample period. There, position data has been adjusted similarly.

2.4 Explanatory power of trading positions

With its regularly published COT report, the CFTC provides some highly valuable data on trading positions. Combining the trading position information from all COT reports published in the period under investigation, one can obtain time series data of the long and short positions of the three types of traders. Now the question is, whether there is a statistically significant relationship between the reported trading positions and the prices of the corresponding futures contracts, and if so, what the nature of this relationship is. As a means to get an insight into the relationship of these two variables, a univariate ordinary least squares (OLS) regression model is proposed. Obviously, trading positions serve as the independent variable while futures prices act as the dependent variable. Note that no attempts to forecast price series are made with this regression model. Instead, patterns in contemporary movements should be detected.

Selecting the right specification of the regression model is not straightforward, however. Theoretically, relating the absolute values of the net trading positions on the absolute prices of the futures contracts would be a possibility. Nevertheless, this specification would lead to spurious correlations because in many cases both, prices and trading positions showed some long-term gains. These long-term trends do not suggest a causal relationship, however. Another option that would avoid this issue is relating changes in futures prices on absolute trading positions. In this case, the explanatory power of the framework would be rather low, however, because a visual analysis of the trading positions time series graphs indicates that reversions from a net long to a net short position and vice versa are protracted processes. In order to avoid these issues it has been decided to investigate the relation between changes in futures contract prices and changes in net trading positions in the corresponding contract.

Therefore, the independent variable is the result of $L_{i,t}^{j} - S_{i,t}^{j} - (L_{i,t-K}^{j} - S_{i,t-K}^{j})$ where L refers to the amount of long contracts held by trader type i (Commercials, Noncommercials and Nonreportables) in futures market j (Corn, Wheat, etc.), S is the amount of short contracts and K denotes the length of the rolling window in time as measured by the amount of trading days. On the other hand, the relative change in price of the futures contract, expressed in the form of the log-return, is used as the dependent variable. Changes in futures prices have been calculated as log returns as this is common practice in finance. Shifts in net trading positions have to be expressed as a difference, however. For trading positions, the calculation of log returns is not feasible because net trading positions will be negative in times when short positions exceed long positions. Following these explanatory notes, the regression model can be expressed as follows:

$$\ln\left(\frac{p_{t}^{j}}{p_{t-K}^{j}}\right) = \alpha_{i}^{j} + \beta_{i}^{j}(L_{i,t}^{j} - S_{i,t}^{j} - L_{i,t-K}^{j} + S_{i,t-K}^{j}) + \varepsilon_{i,t}^{j} \tag{2}$$

On the left side of the equation is the log-return in the period from $t-K$ to t, calculated as the logarithm of the quotient of the price of the futures contract j at point in time t and the price of the same contract at point in time $t-K$. p_{t}^{j} is the settlement price of contract j at point in time t. The right side of the equation is the sum of the constant α_{i}^{j}, the slope coefficient β_{i}^{j} multiplied by the net position of trader type i in futures market j, and the regression error term $\varepsilon_{i,t}^{j}$.

A practical problem is the selection of an appropriate observation period K. By choosing an arbitrary value for K, one decides over which time period the relation between the independent and the dependent variable shall be investigated[7]. However, choosing an arbitrary value for K implies the disadvantage that the degree to which the obtained results can be generalized is limited. In order to mitigate this problem it has been decided to test the relationship for several different observation periods. This method allows seeing whether the obtained results are approximately the same – regardless of K – and therefore provides some information about the robustness of the findings. For this study,

[7] Note that K refers to the period as measured in trading days over which changes in futures contract prices and changes in net trading positions are calculated, as shown in the regression formula. K must not be mistaken for the regression sample which is 15 years.

holding periods of 30, 60, 90, 130 and 260 trading days have been chosen. 130 and 260 trading days correspond to half a calendar year and a full calendar year, respectively. Regressions have been performed for each of the 10 selected futures contracts j, for each of the 3 types of traders i and for each of the 5 selected observation periods K. Multiplying these parameters, the total number of regressions is 150.

Trading position time series are obtained from the CFTC's COT reports and futures prices are the continuous futures prices time series obtained from Datastream, as described in section 2.1. Time series data for futures prices and trading positions are sampled at different frequencies: While settlement prices are available for every trading day, corresponding trading positions are published only every week or every other week, respectively. In order to overcome the problem of differing sampling frequencies, a simple interpolation mechanism is proposed: To each trading day in the sample, the most recent trading position data is allocated. Therefore, trading positions from a COT report are used until it is replaced by its more recent successor.

Table 5 shows the regression results: Panel A displays the results for the trader type (i) Commercials, Panel B those for Noncommercials and Panel C those for Nonreportable traders. The results for the futures contracts (j) are displayed in columns. One the other hand, each line represents an observation period K. For each regression, the slope coefficient β, the coefficient of determination (R^2) and the t-statistic (in parentheses) are reported. A positive β means that the type of trader increases its net position in times of rising contract prices while reducing its exposure in periods of negative returns. A negative β, on the other hand, signifies that the type of trader increases its net position in times of negative returns and decreases its holdings when the futures contract appreciates. Usually, the slope coefficient β shows how, ceteris paribus, the return in the observation period would change if the net position of a trader group is increased by *one* futures contract. Considering the huge amount of futures contracts traded in today's markets, it is obvious that the influence of a single contract – and therefore β – has to be very small. In order to improve readability, reported slope coefficients have been multiplied by 1,000. Reported tabular values therefore represent a change of the net trading position by 1,000 contracts. The values in parentheses are t-statistics under the null hypothesis $\beta = 0$. Durbin-Watson (1950, 1951) residual tests have shown signs of autocorrelation and White (1980) tests have detected signs of heteroskedasticity. Therefore, the t-statistics have been corrected for autocorrelation and heteroskedasticity with the Newey-West (1987) method.

Table 5: Regression results

PANEL A: COMMERCIALS

K	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.0012	(-18.62)	-0.0030	(-17.05)	-0.0015	(-18.16)	-0.0005	(-4.82)	-0.0006	(-17.79)	-0.0009	(-22.82)	-0.0004	(-14.09)	0.0000	(-2.95)	-0.0007	(-16.57)	-0.0031	(-15.53)
	R^2	0.44	***	0.32	***	0.33	***	0.05	***	0.33	***	0.44	***	0.25	***	0.01	***	0.33	***	0.33	***
60 days	β	-0.0014	(-19.76)	-0.0034	(-17.44)	-0.0015	(-12.79)	-0.0006	(-5.07)	-0.0007	(-14.95)	-0.0010	(-22.05)	-0.0004	(-14.01)	-0.0001	(-2.99)	-0.0007	(-15.47)	-0.0033	(-15.66)
	R^2	0.48	***	0.31	***	0.25	***	0.06	***	0.31	***	0.41	***	0.25	***	0.01	***	0.29	***	0.34	***
90 days	β	-0.0014	(-21.88)	-0.0034	(-14.48)	-0.0014	(-10.26)	-0.0008	(-5.50)	-0.0008	(-14.12)	-0.0011	(-16.69)	-0.0005	(-15.41)	-0.0001	(-3.26)	-0.0007	(-14.99)	-0.0034	(-13.35)
	R^2	0.47	***	0.27	***	0.17	***	0.08	***	0.29	***	0.32	***	0.25	***	0.02	***	0.24	***	0.31	***
130 days	β	-0.0014	(-23.14)	-0.0037	(-13.94)	-0.0012	(-6.82)	-0.0008	(-4.52)	-0.0008	(-12.28)	-0.0010	(-13.28)	-0.0005	(-14.62)	-0.0002	(-3.87)	-0.0007	(-13.53)	-0.0034	(-11.69)
	R^2	0.45	***	0.27	***	0.10	***	0.06	***	0.24	***	0.23	***	0.22	***	0.03	***	0.22	***	0.28	***
260 days	β	-0.0014	(-19.85)	-0.0046	(-15.40)	-0.0010	(-4.58)	-0.0009	(-4.38)	-0.0008	(-8.39)	-0.0008	(-6.96)	-0.0006	(-14.51)	-0.0002	(-3.70)	-0.0009	(-9.66)	-0.0036	(-11.24)
	R^2	0.41	***	0.28	***	0.04	***	0.05	***	0.11	***	0.08	***	0.23	***	0.03	***	0.16	***	0.21	***

PANEL B: NONCOMMERCIALS

K	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0012	(16.30)	0.0032	(18.36)	0.0020	(17.94)	0.0004	(2.99)	0.0008	(14.20)	0.0013	(18.97)	0.0004	(11.77)	0.0000	(0.66)	0.0008	(15.42)	0.0032	(15.09)
	R^2	0.40	***	0.32	***	0.33	***	0.01	***	0.27	***	0.39	***	0.18	***	0.00		0.29	***	0.32	***
60 days	β	0.0014	(17.98)	0.0036	(18.65)	0.0019	(13.05)	0.0008	(4.31)	0.0010	(13.18)	0.0015	(19.00)	0.0005	(12.45)	0.0000	(0.66)	0.0008	(14.11)	0.0034	(14.93)
	R^2	0.46	***	0.33	***	0.26	***	0.03	***	0.27	***	0.39	***	0.21	***	0.00		0.26	***	0.33	***
90 days	β	0.0014	(19.98)	0.0038	(17.21)	0.0019	(10.90)	0.0008	(4.35)	0.0011	(12.44)	0.0016	(14.94)	0.0006	(14.46)	0.0000	(1.23)	0.0008	(13.01)	0.0036	(12.84)
	R^2	0.45	***	0.31	***	0.18	***	0.03	***	0.25	***	0.31	***	0.21	***	0.00		0.21	***	0.31	***
130 days	β	0.0014	(20.19)	0.0041	(17.28)	0.0016	(7.60)	0.0008	(3.65)	0.0011	(11.46)	0.0015	(12.89)	0.0007	(14.46)	0.0001	(2.28)	0.0008	(11.20)	0.0037	(11.66)
	R^2	0.43	***	0.33	***	0.12	***	0.02	***	0.21	***	0.23	***	0.21	***	0.01	**	0.19	***	0.28	***
260 days	β	0.0014	(17.81)	0.0053	(21.62)	0.0016	(5.72)	0.0014	(4.78)	0.0011	(7.91)	0.0013	(7.35)	0.0009	(15.21)	0.0001	(3.58)	0.0010	(8.40)	0.0041	(11.63)
	R^2	0.37	***	0.38	***	0.06	***	0.05	***	0.10	***	0.09	***	0.25	***	0.01	***	0.15	***	0.22	***

PANEL C: NONREPORTABLES

K	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0007	(2.09)	0.0019	(2.11)	0.0034	(10.78)	0.0005	(3.40)	0.0020	(21.28)	0.0025	(26.21)	0.0007	(10.21)	0.0001	(4.27)	0.0028	(16.59)	0.0060	(5.57)
	R^2	0.01	**	0.01	**	0.17	***	0.03	***	0.36	***	0.44	***	0.15	***	0.02	***	0.31	***	0.06	***
60 days	β	0.0003	(0.99)	0.0008	(0.87)	0.0032	(7.65)	0.0006	(3.50)	0.0023	(15.64)	0.0027	(21.97)	0.0008	(10.68)	0.0002	(4.30)	0.0028	(14.85)	0.0064	(5.62)
	R^2	0.00		0.00		0.11	***	0.03	***	0.30	***	0.38	***	0.14	***	0.03	***	0.28	***	0.06	***
90 days	β	0.0004	(1.05)	-0.0013	(-1.50)	0.0025	(5.22)	0.0008	(4.12)	0.0026	(14.61)	0.0027	(15.98)	0.0009	(11.01)	0.0002	(3.80)	0.0028	(15.41)	0.0050	(4.59)
	R^2	0.00		0.00		0.05	***	0.04	***	0.28	***	0.29	***	0.13	***	0.02	***	0.24	***	0.03	***
130 days	β	0.0008	(2.45)	-0.0028	(-3.29)	0.0015	(2.71)	0.0008	(3.24)	0.0026	(11.42)	0.0027	(11.57)	0.0008	(8.47)	0.0001	(3.03)	0.0030	(13.91)	0.0028	(2.50)
	R^2	0.01	**	0.02	***	0.02	***	0.03	***	0.23	***	0.20	***	0.09	***	0.01	***	0.20	***	0.01	**
260 days	β	0.0013	(3.30)	-0.0054	(-4.63)	0.0003	(0.47)	0.0007	(2.29)	0.0022	(6.92)	0.0019	(5.66)	0.0007	(5.92)	0.0001	(1.21)	0.0030	(10.85)	0.0034	(2.77)
	R^2	0.03	***	0.05	***	0.00		0.01	**	0.09	***	0.06	***	0.05	***	0.00		0.12	***	0.01	***

Regression equation: (1). Data sources: CFTC COT reports (trading positions), Datastream (contract prices). Sample: 01/01/1992-12/31/2006. To improve readability β regression coefficients have been multiplied by 1,000. Newey-West (1987) adjusted t-statistics under the null hypothesis that $\beta_i^j = 0$ are displayed in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. R^2 is the regression model's unadjusted coefficient of determination.

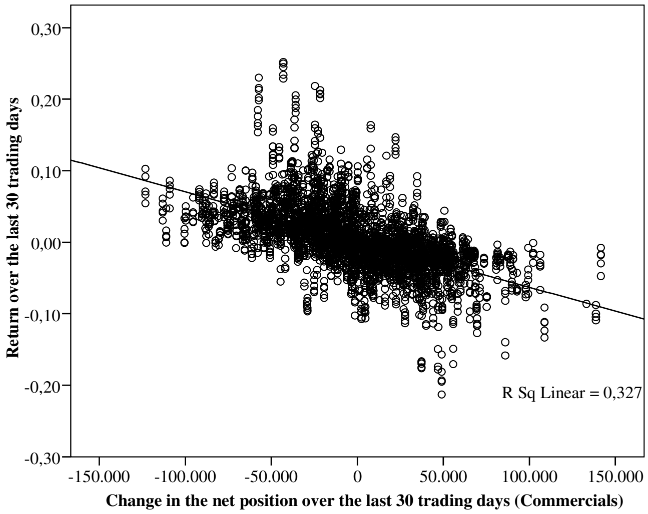
The generally high coefficients of determination suggest that there indeed seems to be a relation between futures returns and changes in net trading positions. In almost all cases the null hypothesis $\beta = 0$ could be rejected at the 1% significance level. Due to the large sample of 15 years, the standard errors of the regressions are low and, consequently, the t-statistics are generally high. Observed R^2 coefficients are especially high for the agricultural and the foreign exchange futures contracts. Only for the Treasury Note contract the explanatory power of the regression is almost zero. In 78 out of 150 cases R^2 exceeded 20%; in 12 instances it was even larger than 40%. In most of the cases, the algebraic sign of β remained stable, regardless of the observation period K. Often, R^2 coefficients declined when K has been increased.

In most instances, the regressions for the commercial trading positions resulted in negative β slope coefficients, while those for Noncommercials and Nonreportables had positive β. These contrarian slope coefficients are not surprising: As futures markets are a zero sum game, slope coefficients have to be opposite. Otherwise, trading positions would not be offset properly. Note that the slope coefficients for different futures markets analyzed can not be directly compared with each other. Considering a $\beta^{Wheat}_{Comm,K=30}$ of -0.0030 and a $\beta^{Oil}_{Comm,K=30}$ of -0.0015 does not imply a greater sensitivity of the Wheat contract toward Commercials' net positions as compared to the Light Sweet Crude Oil contract. In this example, the opposite is the case: When comparing the β^j_i regression coefficients for two different markets, one has to take into account that the two contracts may exhibit considerable differences in open interest. In fact, the Oil contract's open interest is a multiple of its Wheat counterpart. Consequently, it can be concluded that, relatively to open interest, the Oil contract reacts more sensitively towards changes in Commercials' net positions.

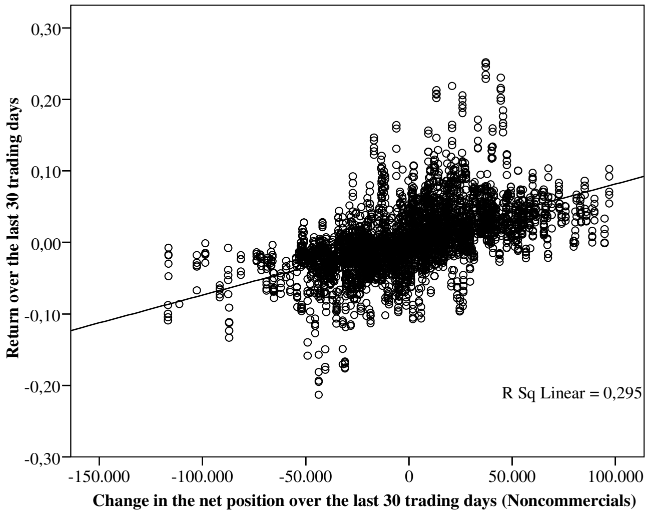
In order to explain the regression results in more detail, the scatter plots for the gold contract with $K = 30$ are displayed in Figure 3. Gold has been chosen because it features high coefficients of determination and therefore produces clear patterns in the scatter plots. The figures show the scatter plots for the Commercials, Noncommercials and Nonreportables, respectively. The x-axis of the scatter plots represents changes in the net positions of the three groups of traders while the y-axis displays the corresponding returns of the Gold contract in the last 30 trading days. Note that changes in the positions of Nonreportables are clearly smaller as compared to Commercials and Noncommercials, which is not surprising because the positions of nonreportable traders in the Gold contract are rather small (confer Figure 1).

Figure 3: Scatter plots

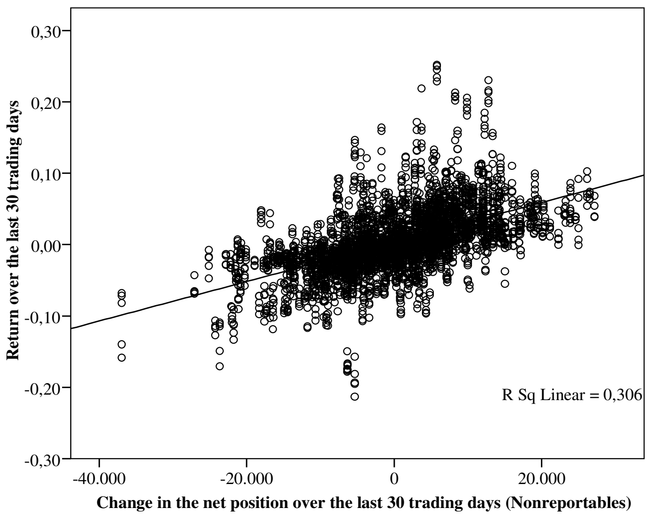
Panel A: Commercials



Panel B: Noncommercials



Panel C: Nonreportables



The group of Commercials for the Gold contract consists of producers and processors of Gold. The negative slope coefficient suggests that producing hedgers are prevailing in this group. An appreciation in the price of the futures contract goes along with a negative change in the net position. That means that the Commercials either enter new short positions or close existing long positions. This behavior would make sense from the view of a hedging producer. As outlined before, producers of a commodity lock in their profits by short-selling contracts on the respective commodity. When the price of the futures contract is climbing, more producers will decide to grasp the opportunity of locking in their revenues at elevated price prices. Therefore, new short positions are entered which reduces the Commercials' overall net position. Falling contract prices, on the other hand, make it less attractive to lock in revenues, which seems to be the reason why Commercials' net position in such periods is increasing.

The positive slope for Noncommercials also seems to make sense from an economic point of view: Positive returns attract more market participants with a speculative trading motive. This pattern could be attributed to a common behavior in financial markets: Trend-following. Middleton (2005), for instance found that "trend-following was the dominant trading style of commodity trading advisors". CTAs are a typical example of Noncommercial traders. The fact that the slope coefficient of Noncommercials and Nonreportables is the same in almost all instances lends further support to the notion that nonreportable traders mainly have a speculative nature.

In summary, Commercials reduce their net positions in periods of rising futures prices and vice versa. In contrary, Noncommercials and Nonreportables tend to increase their net holdings in periods of appreciating futures prices. Due to this contrarian behavior, it is ensured that long and short positions remain offset and sum up to zero.

This section has addressed the behavior of futures traders in rising and falling markets. From the reported results the trading performance of the three groups of traders can not be inferred, however. The results just emphasized the differences in their market behavior. Therefore, the next section is dedicated to measuring the trading performance of the different types of traders.

2.5 Traders' performances

The previous section clearly demonstrated that the three groups of traders differ substantially in their market behavior. It is self-evident that theses differing approaches will in turn lead to different trading performances. Therefore, this section is dedicated to measuring the mean buying and selling prices of the three types of traders. If a type of traders is consistently able to generate a favorable spread between buying and selling prices then this would be interpreted as an indicator of a positive overall trading performance.

The regularly published COT reports show the positions of the three groups of traders. From these reports, time series of net positions for the three groups can be constructed. Combining the net position time series with the futures prices time series, one can find out, at what prices, on average, the groups had been increasing and decreasing their positions. Admittedly, the bi-weekly or weekly position data from the COT reports can only serve as an approximation to high-frequency trading position data. It can not be avoided that very short-term fluctuations in the trading positions can not be incorporated in the analysis. Nevertheless, this observation method allows capturing the secular trends in traders' portfolios. In the following, an improved version of a test proposed by Houthakker (1957) is presented.

Comparing two subsequent COT reports, one can find out how the aggregate holdings of a type of trader have changed. For instance, consider the COT reports for the Swiss Franc contract from April 19, 1994 and April 26, 1994. From the disclosed positioning data it can be calculated that Noncommercials were first net short 5,580 contracts and net short 394 contracts in the second week. It can be concluded that the noncommercial traders, *on aggregate*, must have increased their net holdings by 5,186 contracts in the period from April 19 to April 26, 1994. For lack of any detailed transaction information it is assumed that the buy price for these 5,186 contracts is the mean futures price which prevailed in that period. The mean price is obtained by dividing the sum of the daily settlement prices by the number of days in the period. In the above-mentioned example, the average futures price in the period from April 19 to April 26, 1994 would be calculated. Repeating this procedure for every COT report in the sample period, one can calculate the total expenditures of a group of traders for increasing their net positions. Dividing by the total number contracts purchased in the sample period from 1992 to 2006, one obtains the mean purchase price $\overline{X}$

$$\overline{X} = \frac{\sum_{x=1}^{X} (NP_x^{i,j} - NP_{x-1}^{i,j}) \frac{\sum_{t=1}^{T} p_t^j}{T}}{\sum_{x=1}^{X} NP_x^{i,j} - NP_{x-1}^{i,j}}, \tag{3.1}$$

where $NP_x^{i,j}$ is the net position of trader type i in period x for the futures contract j. X refers to the amount of periods in which trader type i has increased its net position. T refers to the amount of trading days between the release of two COT reports. Similarly, $\overline{Y}$, the mean price at which a type of trader reduced its net positions can be calculated as

$$\overline{Y} = \frac{\sum_{y=1}^{Y} (NP_y^{i,j} - NP_{y-1}^{i,j}) \frac{\sum_{t=1}^{T} p_t^j}{T}}{\sum_{y=1}^{Y} NP_y^{i,j} - NP_{y-1}^{i,j}}, \tag{3.2}$$

where Y is the number of periods in which trader type i has reduced its net position in futures contract j. Transaction costs have been disregarded when calculating mean prices. Table 6 shows the results of the calculations.

Table 6: Mean purchase and sales prices

PANEL A: COMMERCIALS

	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Mean purchase price $(\overline{X})$	244.39	333.52	28.40	908.52	0.8840	0.7224	101.50	103.15	365.77	554.55
Mean sales price $(\overline{Y})$	242.93	337.14	27.98	937.15	0.8756	0.7165	101.20	103.16	361.70	552.12
Price spread	-0.60%	1.09%	-1.47%	3.15%	-0.95%	-0.82%	-0.30%	0.01%	-1.11%	-0.44%
t-Statistic	-0.39	0.72	-0.38	1.17	-1.34	-0.96	-0.45	0.05	-0.66	-0.18

PANEL B: NONCOMMERCIALS

	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Mean purchase price $(\overline{X})$	240.84	337.21	29.50	907.31	0.8752	0.7226	101.02	103.24	365.06	553.51
Mean sales price $(\overline{Y})$	241.46	334.26	29.79	895.94	0.8833	0.7273	101.14	103.08	369.50	556.08
Price spread	0.26%	-0.88%	0.98%	-1.25%	0.92%	0.64%	0.12%	-0.15%	1.22%	0.46%
t-Statistic	0.17	-0.59	0.26	-0.47	1.28	0.76	0.18	-0.78	0.73	0.19

PANEL C: NONREPORTABLES

	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Mean purchase price $(\overline{X})$	249.55	342.19	27.80	988.76	0.8769	0.7070	101.74	103.03	360.65	550.23
Mean sales price $(\overline{Y})$	251.35	339.07	28.29	963.27	0.8842	0.7138	102.14	103.25	362.46	550.59
Price spread	0.72%	-0.91%	1.78%	-2.58%	0.84%	0.96%	0.40%	0.21%	0.50%	0.07%
t-Statistic	0.49	-0.62	0.45	-1.04	1.17	1.11	0.59	1.06	0.30	0.03

Data sources: CFTC COT reports (trading positions), Datastream (futures prices). Sample: 01/01/1992 – 12/31/2006, consisting of 763 weekly/bi-weekly observations. t-Statistics are under the null hypothesis $H_0 : \overline{X} = \overline{Y}$.

The mean purchase price denotes the average price which has been paid for a long contract, while the mean sales price shows at which price the long position has been sold, on average. Similarly, $\overline{Y}$ and $\overline{X}$ show the prices at which short positions have been entered and settled, respectively. Moreover, reported price spreads measure the difference between $\overline{X}$ and $\overline{Y}$. To assess the statistical significance of the price spreads, a pooled variances t-test[8] is performed. Reported t-statistics are under the null hypothesis $H_0 : \overline{X} = \overline{Y}$.

Results show that hedgers had negative performances in 7 out 10 futures contracts. The three exceptions are the Wheat, S&P 500 and the Treasury Note contracts. Commercials have made some large gains in the S&P 500 future but have lost noticeably in the Light Sweet Crude Oil contract, on

[8] t-Statistics have been calculated with the pooled-variances formula $t = \frac{(\overline{x}_1 - \overline{x}_2)}{\sqrt{s_p^2(\frac{1}{n_1} + \frac{1}{n_2})}}$ with $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$ and $df = n_1 + n_2 - 2$. For a derivation of the pooled variances t-test see for example Gönen et al. (2005).

average. Noncommercials and Nonreportables, on the other hand, have realized positive returns in most of the cases: Noncommercials have sold their futures contracts at price levels that were higher than their acquisition prices, on average, in 7 out of 10 markets analyzed. For Nonreportables the same finding applies to even 8 out 10 contracts. None of the price spreads are statistically significant however. Due to low t-statistics, the null hypothesis could not be rejected in any of the markets. Because of the low data sample frequency (bi-weekly and weekly), the amount of $n = 763$ observations is rather low, considering the long sample period of 15 years. Standard errors would be considerably lower if trading position data was available at higher frequencies. Therefore, chances are that the null hypothesis could not be rejected because the power of the test is too low. Even if not statistically significant, the obtained results are interesting, nevertheless. Again, Commercials on the one hand and Noncommercials and Nonreportables on the other hand had opposite results.

Reported findings are mostly consistent with the results of Houthakker (1957) who analyzed the data for the corn, wheat and cotton futures markets from 1937 to 1952. He found that "in all three commodities the large hedgers lost and the large speculators gained. The small traders lost in the grains but did quite well in cotton." Therefore, the obtained results differ only with regards to the wheat contract where – in contrary to Houthakker – positive returns to hedgers have been identified. An explanation for these differing results will be given in section 3.2 of this thesis.

Academic literature mentions two concepts that could explain differences in the futures trading performance among the different types of traders: Risk premia and superior forecasting abilities (Kamara, 1982). The next two sections are dedicated to these concepts. In both cases, explanations of the concepts are followed by empirical an empirical analysis.

2.6 Test for risk premia

The first explanation of how spot prices and futures prices are linked is accredited to Keynes (1930):

> *If supply and demand are balanced, the spot price must exceed the forward price by the amount which the producer is ready to sacrifice in order to 'hedge' himself, i.e. to avoid the risk of price fluctuations during his production period. Thus in normal conditions the spot price exceeds the forward price, i.e. there is a backwardation. In other words, the normal supply price on the spot includes remuneration for the risk of price fluctuations during the period of production, whilst the forward price excludes this.*

Keynes' notion has generally become known as the theory of normal backwardation. According to this theory, hedgers have to pay a premium to the speculators for their willingness to bear the risk of price fluctuations by engaging in a futures contract. Similarly, the role of a speculator in the futures market can be compared to an insurer, according to Keynes. In this way, speculators would earn their premium by engaging in a long position at a time prior to the delivery month. The premium is forwarded to speculators by the market price mechanism: If, as Keynes assumed, the spot price exceeds the futures price, speculators would earn their premium by entering into the futures contract at the lower futures price and eventually settling the contract in the delivery month when the futures price equals the spot price. Between the time of engaging in the contract and the time of settlement, the futures price is expected to converge to the spot price, as both entitle a claim to the similar asset at delivery time. Provided that the price of the underlying commodity does not decline significantly, the speculator earns the price difference between the engaging and the settling price as his premium. On the other hand, this price differential can be viewed as the price that hedgers have to pay to hedge against price fluctuations. Other things equal, the higher this price difference, the less likely it is that they will engage in hedging positions. Chang (1985) defines the risk premium as "an average reward to investors for being willing to assume a risk position in a risk-averse financial world. The reward in this form should not be conditional on any superior judgment or inside information." According to Gray (1969) the "risk premium must be the difference between futures prices and expected prices. Keynes' theory has been supported by Hicks (1939) who explicitly addressed the function of speculators in futures markets. Hicks has acknowledged speculators as market participants who act as counterparty in cases of excess supply or demand for futures contracts. Moreover, he describes the role of speculators in the pricing process:

> *The futures price [...] which would be determined by causes that have nothing to do with the causes ordinarily determining market price; it would therefore be widely different from the spot price which any sensible person would expect to rule in a month's time, and would ordinarily be much below that expected price. [...] [Speculators'] action tends to raise the futures price to a more reasonable level.*

Three assumptions form the basis of the theory of normal backwardation (Chatrath, Liang, & Song, 1997):

1. Speculators are risk averse.
2. Hedgers are net short (and speculators net long).
3. Speculators do not have forecasting abilities.

The classic assumption that hedgers are net short can be disproved empirically by referring to reports of aggregated trading positions. In fact, both, markets with hedgers being net short as well as the opposite can be found in reality. In this context, an important contribution has been made by Cootner (1960) who developed an economic model that relaxes the assumption of hedgers being net short on a constant basis. He showed that the theory of normal backwardation does not conflict with contango situations, given that hedgers have a net long position. The third assumption's purpose is to facilitate tests for risk premia. By assuming that speculators do not have any forecasting ability regarding the future development of prices, any positive returns would, by definition, be risk premia.

Telser (1958), Rockwell (1964) and Hartzmark (1984) contend an alternative view that contradicts to the theory of normal backwardation. In this notion, risk premia can not exist because as soon as there would be any risk premium, it would be bid down to zero by speculators. As a result, the supply of speculative services would be horizontal at a zero rate of return. According to Hartzmark (1987), "factors such as luck, superior forecasting ability, or market power determine the relative rewards individuals gain in the futures market". The role of speculators is seen in "providing liquidity and enhancing the efficiency of the price discovery function that futures markets fulfill" (Hartzmark, 1987). Any positive returns to speculators would come from superior forecasting skills, market power or simply luck (Leuthold et al., 1994). It is without controversy that the major groups participating in futures trading are hedgers and speculators. Any theory trying to explain returns in futures markets must therefore be able to explain the long lasting presence of these groups in the markets. Keynes' theory of normal backwardation argues that hedgers participate in futures trading because this allows them to offset risk. Speculators, on the other hand, trade because they get compensated for their "insurance services". Consequently, both groups benefit from their activities in the markets. In the alternative view of Telser and others, it is not self-evident why speculators would participate in the markets, as they do not earn any profits, according to this theory. Assuming that the alternative theory of Telser and other would fully apply to the real futures markets, possible explanations for consistent inflow of speculators could be their "irrational" belief of having superior skills or simply their "desire to gamble in the markets" (Hartzmark, 1991).

Formally, the concept of risk premia can be written as follows (Fama & French, 1987):

$$F_{t,T} - S_t = E_t[P_{t,T}] + E_t[S_T - S_t] \tag{4.1}$$

"The difference between the futures price and the current spot price can be expressed as the sum of an expected premium and an expected change in the spot price" (ibid.). Straightforward transformations lead to:

$$E_t[P_{t,T}] = F_{t,T} - E_t[S_T] \tag{4.2}$$

Thus, the "expected premium is defined as the bias of the futures price as a forecast of the future spot price" (Fama & French, 1987). Risk premia themselves, in turn, can be viewed as rewards for two separate components: Systematic risk and hedging pressure (de Roon, Nijman & Veld, 2000). Systematic risk is measured as the "covariance between the futures returns and the market return and other economic aggregates", while hedging pressure "results from risks that agents cannot, or do not want to trade because of market frictions such as transaction costs and information asymmetries" (ibid.). The existence of risk premia has been subject of a considerable academic debate. In addition to the above-mentioned debate on the theoretical foundations of risk premia, the mixed empirical results have impeded consensus building.

In an analysis of the Corn contract, Gray (1969) was unable to find a price bias. Changing his test methodology, he detected significant signs of risk premia, however. A paper by Dusak (1973) concentrated on the investigation of the systematic risk component using the well-known CAPM approach. In the analyzed wheat, corn and soybean futures contracts, realized returns over the sample period were close to zero. Therefore, no evidence for the existence of a compensation for bearing market risk has been found. Hartzmark (1987) presented strong evidence against risk premia and therefore against the theory of normal backwardation. For his study, Hartzmark had access to a 4½ years sample of non-public disaggregated trading data provided by the CFTC. He found that Commercials earned about 85% of the total net profits earned by all types of traders. What is even more strikingly about his results is that the most successful 0.1% of the traders (all off them were Commercials) earned 58% of the total net profits. Hence, he concluded that "hedgers are getting paid while they reduce their risks, quite the contrary to the theory of normal backwardation". As opposed to Hartzmark, Bessembinder (1992) found that "results in foreign currency and agricultural futures vary with the net holding of hedgers, after controlling for systematic risk. These results [...] support hedging pressure as a determinant of futures premiums."

In order to come up with an explanation of price spreads in the observed futures markets, a test for risk premia is proposed. For the test it has been decided to adopt the naïve trading strategy by Chatrath, Liang & Song (1997) because this approach is highly intuitive and bases on well-founded assumptions. As outlined earlier, returns to traders can consist of risk premia and rewards for superior forecasting skills. The fundamental idea of the naïve trading strategy is to filter out the effects of potentially existing forecasting abilities from the returns to traders. This way, the undistorted risk premium should be discovered. In order to filter out the forecasting skills, a mechanical trading strategy has to be pursued: A naïve trader is long one contract if hedgers are net short and is short one contract if hedgers are net long (Chatrath, Liang & Song, 1997). With this strategy the naïve trader constantly provides insurance services for the hedgers, regardless of their net position. Due to the inflexible nature of the strategy, rewards for forecasting skills can be ruled out. Therefore it is assumed that the pay-off of this trading strategy is the "pure" risk premium.

Table 7: Results of the naïve trading strategy

Futures contract	Risk premium (r)	t-Statistic		Number of long periods	Number of short periods	Trading days long	Trading days short
Corn	0.64%	(0.18)		22	21	1,417	1,712
Wheat	-15.65%	(-4.09)	†††	23	23	2,054	1,075
Oil	0.32%	(0.08)		39	39	1,878	1,251
SP500	-12.62%	(-5.99)	†††	31	31	1,943	1,186
JPY	2.81%	(1.84)	*	28	29	946	2,183
CHF	-3.57%	(-2.47)	††	31	32	1,158	1,971
Bond	-2.81%	(-2.66)	†††	37	38	1,836	1,293
Note	-0.47%	(-1.89)	†	35	35	863	2,266
Gold	4.44%	(2.03)	**	21	21	1,922	1,207
Silver	8.06%	(0.32)		1	0	3,129	0

Data source: CFTC COT reports (trading positions), Datastream (futures prices). Sample: 01/01/1992 – 12/31/2006. Reported t-statistics (in parentheses) are under the null hypothesis $H_0 : r_j^i = 0$. * and ** denote statistically significant positive returns at the 10% and 5% levels. †, †† and ††† denote statistically significant negative returns at the 10%, 5% and 1% levels.

Implementing the specifications of the strategy means that the trading position (either one contract long or one contract short) is revised every time new information about hedgers' net position is available. In practice, this means that the trading position of the naïve trader is updated every time a new COT report is released.

Table 7 shows the results of the naïve trading strategy. Apart from the earned risk premia [as defined by Chatrath, Liang & Song (1997)] and corresponding t-statistics, the table also shows in how many periods and trading days the naïve trader has been long and short, respectively. It is found that in half of the futures markets analyzed the return to the naïve trader – and therefore the risk premium – is actually negative. All the negative returns are statistically significant at least at the 10% level. With regards to the contracts with positive risk premia it is found that only the returns in the Japanese Yen and the Gold futures contracts are statistically significant. These results can be interpreted in two ways:

First, it could be reasoned that the obtained results signalize market segmentation. In this notion, positive risk premia would only prevail in a subset of futures markets. The obtained results coincide completely with those in Chatrath, Liang & Song (1997). In this paper the wheat, soybeans, corn, coffee and cotton futures markets were analyzed. There, the hypothetical naïve trader also gained either positive or negative risk premia, depending on the contract investigated. By all means, the obtained results lend no clear support to Keynes' (1930) theory of normal backwardation.

Secondly, one could doubt that the proposed naïve trading strategy is a valid method to capture risk premia. In this regard, the problem is that no commonly accepted definition of risk premia let alone a widely supported methodology of measuring risk premia exist to date: "[…] the issue of premia is due largely to the fast [sic!] that much guesswork is involved in determining what are returns and what are premia." (Chatrath, Liang & Song, 1997). As the test for risk premia failed to provide any clear results, there is nothing else for it but to investigate another possible explanation for the observation that trading returns seem to differ among the different types of traders. Consequently, traders' forecasting abilities are investigated in the next section.

2.7 Test for forecasting abilities

Even if a type of trader would not earn any risk premia, positive returns could still be explained by superior forecasting skills. This means that a trader would be able to anticipate moves in futures prices to some extent. As a result of his forecasting skills, he would be able to make correct trading decisions more often than one would expect from a random outcome. Such forecasting abilities could be attributed to insider information that is available to the trader, exceptional market timing aptitude or simply luck.

The question of forecasting abilities was first addressed by Houthakker (1957): "In commodity futures markets a measure of the forecasting ability of speculators is not hard to find, for it is immediately reflected in their profits and losses. Except for hedgers […] the buying and selling of futures contracts has no purpose other than to profit from changes in futures prices." Chang (1985) analyzed the Corn, Soybeans and Wheat futures. He was only able to detect forecasting abilities of large traders in the latter contract, however. A study by Hartzmark (1991) reasoned that "the fortunes of individual traders are determined by luck, not forecasting ability". Leuthold, Garcia & Lu (1994) presented an in-depth analysis of the Frozen Pork Bellies futures contract. They found that speculators in this market "not only were able to anticipate the direction of market changes but were on the right side of the market when large changes occurred". In a study of Sanders, Boris & Manfredo (2004), no significant results with regards to forecasting abilities were reported.

It has been decided to analyze traders' forecasting abilities using a methodology that has originally been developed by Henriksson and Merton [see Merton (1981) and Henriksson & Merton (1981)] and has been adapted for the use in futures markets by Chang (1985). While other tests for forecasting abilities may exist, the advantage of the Henriksson-Merton (thereafter referred to as HM) test is the fact that it is a nonparametric procedure and therefore does not make any assumptions with regards to the distribution of returns in futures markets. For lack of space, the concept of the HM test can only be briefly summarized. For a detailed explanation of the test procedure refer to Merton (1981), Henriksson & Merton (1981) and Chang (1985). The latter also explains the fundamental ideal of the test: "The rational behavior of risk-averse speculators in futures markets can be described as follows: They will only be long futures contracts at prices below those expected at the anticipated liquidation time or will be short such contracts at prices above those prevailing at the expected offset period". This means that at point in time t with a current futures price Z_t, a trader with a speculative nature makes a forecast that can be either $Z_{t+K} \le Z_t$ or $Z_{t+K} > Z_t$. The speculator will then enter a long position if he believes that the futures price will rise over the next K trading days or enter a short position if he thinks that the opposite will be the case. To indicate the speculator's conjecture, the forecast variable γ_t is introduced. $\gamma_t = 1$ if the speculator is net long (and therefore anticipates an appreciation in futures prices) and $\gamma_t = 0$ otherwise. Combining the time series of net trading positions and futures returns, one can calculate the conditional probabilities of a correct forecast: $p_{1,t} \equiv \Pr(\gamma_t = 0 | Z_{t+K} \le Z_t)$ is the conditional probability of a correct forecast in periods with negative futures returns and $p_{2,t} \equiv \Pr(\gamma_t = 1 | Z_{t+K} > Z_t)$ is the conditional probability of a correct forecast in periods with positive futures returns. According to HM, a market participant demonstrates statistically significant forecasting abilities if the null hypothesis $H_0 : p_{1,t} + p_{2,t} = 1$ can be rejected. In the above-mentioned papers, Henriksson and Merton show that the null hypothesis can be tested by means of the hypergeometric distribution. In simple terms, the significance of the conditional probabilities is determined by summing up the probabilities for all possible outcomes that are worse than the actual trading performance. For instance, if 8 out of 10 forecasts of a trader have been correct, then the probabilities of up to 7 correct forecasts would be summed up. The probabilities of single outcomes[9], in turn, are obtained from the hypergeometric distribution. If the sum of the probabilities of the worse-than-realized outcomes would be, say 0.90, then it could be reasoned, according to HM, that the trader showed positive forecasting skills at the 10% significance level. If, in turn, the probabilities of the worse-than-realized performances would add up to a significantly small value like, say 0.05, then HM would conclude that the trader actually exhibited a trading performance that signifies *negative* forecasting skills at the 5% level. A detailed mathematical derivation of the significance test with the help of the hypergeometric distribution can be found in Henriksson (1981).

Returns in 6 out of the 10 markets analyzed were negatively skewed, as shown in Table 3. Considering that the number of periods with positive returns and those with negative returns do not differ substantially, the effect of any positive or negative skews would be negligible[10]. It must also be argued that significantly positive results in the HM test are only a necessary but not a sufficient condition to reason that a market participant possesses forecasting abilities: The significantly positive performance could also be attributed to risk premia. Thus, a trader must simultaneously fail to earn any risk premia and show a significantly positive performance in the HM test to prove forecasting skills. Alternatively, significantly negative risk premia that go along with an insignificant result in the HM test would be an indicator of forecasting skills. Therefore, the results of the test for risk premia of the previous section and the results of the HM test must be interpreted collectively in order to come up with any conclusions. The reason for this additional condition is that the HM test has not developed for the use in futures markets, originally.

Table 8 shows the results of the HM test[11]. Panel A presents an overview of the intervals in the sample period from 01/01/1992 to 12/31/2006. A new interval is created each time a new forecast is made. In practice, this means that the number of intervals equals the number of COT reports that have been released in the sample period. Trading positions for the Light Sweet Crude Oil future, for instance, have been reported 761 times during the sample period of 15 years. In 423 out of 761 intervals the Oil futures gained in value or remained unchanged while it lost in the remaining 338 instances. The differences among futures contracts for N arise because in some occasions, not all of the 10 contracts have been part of the COT report. Panels B to D show the results of the HM test for the three types of traders as categorized by the CFTC. For each type of trader it is distinguished between four possible cases: 1. "Correct" forecast in a declining market, 2. "wrong" forecast in a declining market, 3. "correct" forecast in an expanding market, 4. "wrong" forecast in an expanding market.

[9] For instance, the probability of 0, 1, 2, 3 etc. correct predictions.

[10] Because the effects on $p_{1,t}$ and $p_{2,t}$ would roughly balance.

[11] Note that the results for the Silver contract have not been reported. The HM test was not applicable to the Silver market because for this contract, Commercials have been net short during the whole observation period without any exceptions. Therefore, only one forecasting interval has existed in this market.

Table 8: Results of the Henriksson-Merton test

PANEL A: PERIODS

Number of periods	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold
$N = N_1 + N_2$	771	763	761	763	763	761	763	762	762
$N_1 \equiv Z_{t+K} \le Z_t$	399	391	338	337	417	392	350	379	367
$N_2 \equiv Z_{t+K} > Z_t$	372	372	423	426	346	369	413	383	395

PANEL B: FORECASTING ABILITIES OF COMMERCIALS

Realization	Predicted	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold
$Z_{t+K} \le Z_t$	$Z_{t+K} \le Z_t$	180	273	193	182	126	149	195	100	219
	$Z_{t+K} > Z_t$	219	118	145	155	291	243	155	279	148
$Z_{t+K} > Z_t$	$Z_{t+K} > Z_t$	196	118	177	216	229	213	179	280	144
	$Z_{t+K} \le Z_t$	176	254	246	210	117	156	234	103	251
$p_{1,t} \equiv \Pr(\gamma_t = 0 \mid Z_{t+K} \le Z_t)$		0.45	0.70	0.57	0.54	0.30	0.38	0.56	0.26	0.60
$p_{2,t} \equiv \Pr(\gamma_t = 1 \mid Z_{t+K} > Z_t)$		0.53	0.32	0.42	0.51	0.66	0.58	0.43	0.73	0.36
$\sum_{x=\underline{n}_1}^{n_1-1} \frac{\binom{N_1}{x}\binom{N_2}{n-x}}{\binom{N}{n}}$		0.25	0.65	0.36	0.89	0.13	0.10	0.37	0.41	0.12

PANEL C: FORECASTING ABILITIES OF NONCOMMERCIALS

Realization	Predicted	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold
$Z_{t+K} \le Z_t$	$Z_{t+K} \le Z_t$	138	170	141	279	294	251	164	167	170
	$Z_{t+K} > Z_t$	261	221	197	58	123	141	186	212	197
$Z_{t+K} > Z_t$	$Z_{t+K} > Z_t$	231	205	263	72	124	146	199	196	234
	$Z_{t+K} \le Z_t$	141	167	160	354	222	223	214	187	161
$p_{1,t} \equiv \Pr(\gamma_t = 0 \mid Z_{t+K} \le Z_t)$		0.35	0.43	0.42	0.83	0.71	0.64	0.47	0.44	0.46
$p_{2,t} \equiv \Pr(\gamma_t = 1 \mid Z_{t+K} > Z_t)$		0.62	0.55	0.62	0.17	0.36	0.40	0.48	0.51	0.59
$\sum_{x=\underline{n}_1}^{n_1-1} \frac{\binom{N_1}{x}\binom{N_2}{n-x}}{\binom{N}{n}}$		0.15	0.32	0.85	0.42	0.96 **	0.83	0.08 †	0.08 †	0.93 *

PANEL D: FORECASTING ABILITIES OF NONREPORTABLES

Realization	Predicted	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold
$Z_{t+K} \le Z_t$	$Z_{t+K} \le Z_t$	356	117	194	78	273	239	169	311	47
	$Z_{t+K} > Z_t$	43	274	144	259	144	153	181	68	320
$Z_{t+K} > Z_t$	$Z_{t+K} > Z_t$	39	253	187	306	126	153	221	60	333
	$Z_{t+K} \le Z_t$	333	119	236	120	220	216	192	323	62
$p_{1,t} \equiv \Pr(\gamma_t = 0 \mid Z_{t+K} \le Z_t)$		0.89	0.30	0.57	0.23	0.65	0.61	0.48	0.82	0.13
$p_{2,t} \equiv \Pr(\gamma_t = 1 \mid Z_{t+K} > Z_t)$		0.10	0.68	0.44	0.72	0.36	0.41	0.54	0.16	0.84
$\sum_{x=\underline{n}_1}^{n_1-1} \frac{\binom{N_1}{x}\binom{N_2}{n-x}}{\binom{N}{n}}$		0.40	0.24	0.64	0.05 ††	0.68	0.73	0.66	0.17	0.11

Data source: CFTC COT reports (trading positions), Datastream (futures prices). Sample: 01/01/1992 – 12/31/2006. * and ** denote positive forecasting abilities at the 10% and 5% significance levels. †, and †† denote negative forecasting abilities at the 10% and 5% significance levels.

In the example of the Oil future, hedgers have been positioned "correctly" in 193 out of 338 intervals of an expanding market. On the other hand, they have only been positioned "correctly" in 177 out of 423 cases when futures prices declined. For each of the four cases the numbers of the corresponding observations are indicated. The conditional probabilities $p_{1,t}$ and $p_{2,t}$ are shown as well. These probabilities are simply calculated by dividing the "correct" forecasts by the number of applicable intervals. For the Oil future the conditional probability of a correct forecast in an interval of declining futures prices has been $\frac{193}{193+145} = 0.57$. Finally, the significance level (as described earlier) is presented. Values equal to or below 0.10 would – according to HM – signify negative forecasting skills at the 10% level while values equal to or above 0.90 represented positive forecasting abilities at the 10% level.

For commercial traders the results for all markets are statistically insignificant. It is noteworthy, however, that with the exception of the Wheat and the S&P 500 all significance levels have been below 0.50. In the case of the Swiss Franc future the 10% significance level has been missed only slightly[12]. This means that, even if the results are not significant, it still can be seen that on average, Commercials have been "wrong" more often than "right". The results for noncommercial traders are mixed. Significantly positive results have been detected for the Japanese Yen and the Gold future. On the other hand, significantly negative results can be observed for the two interest rate futures. Interestingly, both $p_{1,t}$ and $p_{2,t}$, have been below 0.50 for the Treasury Bond future. Consequently, Noncommercials had a negative trading performance for this contract regardless of the prevailing market regime. Usually, conditional probabilities that were below 0.50 in one market regime have been offset at least partly by a conditional probability greater than 0.50 in the opposite market regime. For nonreportable traders only one result is statistically significant. In the S&P 500 future, Nonreportables exhibited a negative forecasting performance that is significant at the 5% level.

In order to come up with conclusions about forecasting abilities, the results from the HM test must be linked with the results of the naïve trading strategy (see Table 7). Forecasting skills are only proven in two cases: 1. If significantly positive results in the HM test coincide with insignificant or significantly negative results for the naïve trading strategy. 2. If insignificant results from the HM coincide with significantly negative results from the naïve trading strategy.

For Noncommercials, the Japanese Yen and the Gold futures would be possible candidates for case 1. A comparison with the results in Table 7 reveals, however, that a naïve trader who by definition does not have any forecasting abilities managed to earn statistically significant returns in exactly these two markets. Thus, the positive results in the HM test must be attributed to the existence of risk premia and not to forecasting skills. Considering the results for Noncommercials in case 2, however, it can be concluded that the Wheat, S&P 500 and Swiss Franc futures contracts fulfill all required criteria. Therefore it is proven that Noncommercials exhibited forecasting abilities in these markets. For

[12] The exact significance level is 0.8987.

Nonreportables, forecasting skills in the Wheat, Swiss Franc, Treasury Bond and Treasury Note futures have been identified. In addition, Nonreportables have demonstrated forecasting skills in the two interest rates contracts. For hedging market participants, no link to the results of the naïve trading strategy can be drawn as they do earn any risk premia, by definition. Obtained results coincide with the findings of Chang (1985) who detected forecasting abilities among large traders in the Wheat future but failed to prove those skills in the Corn contract.

Chapter 2 has investigated the performance of futures traders and their market behavior. To this end, the market activities of traders in different market regimes have been analyzed by means of a regression framework. Then, the components of trading returns have been studied empirically. The research question whether futures returns in subsequent periods can be inferred from current trading positions is the topic of the next chapter.

3 Investor sentiment index

3.1 Description of the sentiment index

Based upon the findings from section previous analyses it can be supposed that there is a link between trading positions and futures returns: Section 2.4 has shown that traders take positions depending on market returns. Further tests provided evidence for risk premia and forecasting abilities in some of the markets under investigation. As a next step, an investor sentiment index is presented. Then it will be tested if the sentiment index is a reliable indicator of futures returns in subsequent periods.

Sentiment indices are a well-established means of research in a number of disciplines. In economics, sentiment indices are used for forecasting macroeconomic variables. Well-known examples are the Survey of Professional Forecasters (Federal Reserve Bank of Philadelphia, 2007) and the Consumer Sentiment Index of the University of Michigan (2007) for the U.S. as well as the ZEW Indicator of Economic Sentiment (Zentrum für Europäische Wirtschaftsforschung, 2007) and the ifo Business Climate Indicator (ifo, 2007) for Germany. Traditionally, the question whether such indices can be used to forecast economic developments has been subject of empirical research [see for example Cotsomitis & Kwan (2006), Huth, Eppright & Taube (1994), Nahuis & Jansen (2004) and others]. Albeit less common, sentiment indices also play a role in financial markets. The Bearish Sentiment Index, for instance, sets the number of bearish investment advisers in relation to the total number of interviewed investment advisers (Solt & Statman, 1988). Sentiment indices also play a role in futures markets: These indices use the trading position data from the COT reports to get an idea of the sentiment of the three types of traders. Several different ways of measuring investor sentiment in futures markets have been presented in academic papers [see for example Wang (2001, 2003) and Sanders, Boris & Manfredo (2004)]. It also seems like some practitioners base their market timing decisions on the trading position data from the COT reports [confer Welling (1998) and Ruggiero (2002)]. There are two factors that emphasize the expressiveness of a sentiment index that bases on COT data: First, unlike other sentiment indices, COT-based indices are calculated from data that encompasses all market participants. Other indices, in contrary, mostly base on surveys with much smaller samples sizes. Second, COT-based indices are calculated from real market *actions* while other indices base only on interviewee's expressed *opinions*.

It has been decided to use the sentiment index proposed by Wang (2003) for the following empirical analysis because this seems to be the most commonly used index in academics and in the marketplace. The index is calculated as

$$SI_t^{i,j} = \frac{NP_t^{i,j} - \mathrm{Min}\left(NP_t^{i,j}\right)}{\mathrm{Max}\left(NP_t^{i,j}\right) - \mathrm{Min}\left(NP_t^{i,j}\right)} \tag{5}$$

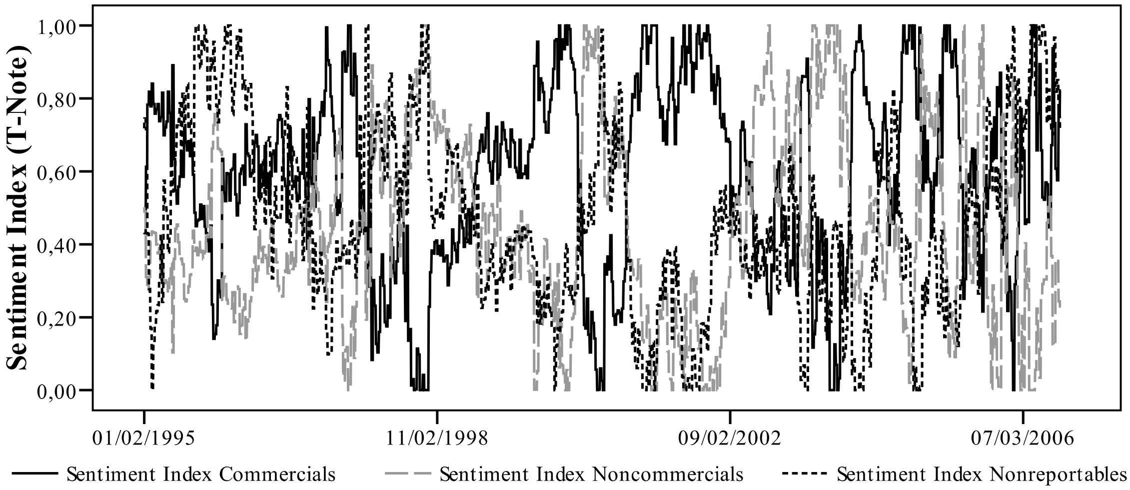
where $NP_t^{i,j}$ denotes the net position of trader type i in futures market j at point in time t. $\mathrm{Min}\left(NP_t^{i,j}\right)$ and $\mathrm{Max}\left(NP_t^{i,j}\right)$ represent the minimum and the maximum of the net position of trader type i in futures market j over a 3 years[13] long rolling window up to point in time t. From the formula it can be seen that the difference between the current net position and the minimum net over the preceding 3 years is calculated. Then this difference is normalized by dividing by the range of the preceding 3 years. Due to the composition of the formula, the sentiment index requires a lead time of 3 years before the first realizations can be calculated. The result is an index that oscillates between 0 and 1. A value of 0 means that the net position of trader type i has reached the lowest level in 3 years. In contrary, a value of 1 signifies that the current net position is the largest in 3 years. Consequently, the index can be interpreted as an indicator for the bullishness of the group of traders. For each futures contract j there are 3 sentiment indices One for Commercials, one for Noncommercials and one that is based on the trading positions of Nonreportables.

Figure 4 displays the 3 sentiment indices for the Treasury Note futures contract. The time series move in opposite directions, as expected. Whenever a group of traders has a net position that is high as compared to the long-term average, this must be accompanied by another trader type having a rather small net position because all long and short positions in the market must remain offset.

Table 9 shows a correlation matrix of the sentiment indices in the 10 single markets and on a portfolio basis. The latter is simply an average of the correlation coefficients of the 10 contracts. Sentiment index time series for Commercials and Noncommercials exhibit a strongly negative correlation, as already shown in Figure 4. In all markets there is as also a negative relation between the sentiment for Commercials and Nonreportables.

[13] The 3 years lenght of the rolling window is an arbitrary value. An investigation of several futures markets magazines has shown that this value seems to best practice, however. The empirical analyses of chapters 3 and 4 have also been tentatively conducted with other values. Results (not reported in this thesis) did not differ substantially from those for a 3 years long rolling window.

Figure 4: Sentiment indices for the Treasury Note futures contract



Data source: CFTC COT reports. Sample: 01/01/1992 – 12/31/2006. Sentiment indices reported as of 01/01/1995.

Table 9: Correlation matrix of the sentiment index

Contract		Noncommercials	Commercials
Corn	**Commercials**	-0.95	1.00
	Nonreportables	-0.18	-0.08
Wheat	**Commercials**	-0.87	1.00
	Nonreportables	-0.28	-0.17
Oil	**Commercials**	-0.97	1.00
	Nonreportables	0.57	-0.74
SP500	**Commercials**	-0.59	1.00
	Nonreportables	0.02	-0.74
JPY	**Commercials**	-0.97	1.00
	Nonreportables	0.67	-0.81
CHF	**Commercials**	-0.98	1.00
	Nonreportables	0.87	-0.93
Bond	**Commercials**	-0.92	1.00
	Nonreportables	0.39	-0.69
Note	**Commercials**	-0.84	1.00
	Nonreportables	0.12	-0.55
Gold	**Commercials**	-0.99	1.00
	Nonreportables	0.75	-0.81
Silver	**Commercials**	-0.98	1.00
	Nonreportables	0.31	-0.42
Portfolio	**Commercials**	-0.91	1.00
	Nonreportables	0.32	-0.59

Data source: CFTC COT reports. Sample: 01/01/1995 – 12/31/2006.

The relation between the sentiment indices of Noncommercials and Nonreportables is depending on the market, but is positive on average. Using the investor sentiment index instead of net positions to forecast futures returns has several advantages (Wang, 2001): "The sentiment index provides a more-intuitive reading of trader actions than the number of long or short contracts" and "this measure of investor sentiment allows for comparisons of return predictability across futures markets, while raw positions make he comparisons impossible due to the diverse structure across futures markets". The latter problem has been in a similar form in section 2.4. There, β slope coefficients could net be compared across different futures contracts because of differing open interests. In the following analysis, this issue will not reappear because the sentiment index has been normalized by dividing by the historical range. Compared to heavily discussed issues like the existence of risk premia and forecasting abilities among traders, the problem of using trading positions to forecast futures returns has seldom been addressed. Previous research observed market transactions from an internal point of view. So far, Wang (2001, 2003) and Sanders, Boris & Manfredo (2004) are the only authors to tackle the issue from an external point of view. In simple terms, previous research tried to find answers to the question "Who wins and why?". Wang's publications, in contrary, rose the question "How can this knowledge be used to win?". In Wang (2001) it is concluded that "large speculator sentiment predicts price reversals" while "large hedger sentiment predicts price reversals. Small trader sentiment was found not to predict anything. The study analyzed the corn, soybeans, soymeal, wheat, cotton and world sugar futures contracts. Extending his methodology on the S&P 500 future, Wang (2003) found similar patterns: "Large speculator sentiment is a price continuation indicator, whereas large hedger sentiment is a contrary indicator". Again, small trader sentiment turned out not to be useful for forecasting purposes. Sanders, Boris & Manfredo (2004) analyzed the crude oil, unleaded gasoline, heating oil, and natural gas futures contracts. They found "a positive correlation between returns and positions held by noncommercial traders, and a negative correlation between commercial positions and market returns".

3.2 Predictive power of the sentiment index

To estimate the predictive power of the sentiment a univariate ordinary least square (OLS) regression model is proposed. In this model the sentiment index of each type of trader serves as the independent variable whereas futures prices act as the dependent variable. The regression equation can be expressed as follows:

$$\ln\left(\frac{p_{t+K}^{j}}{p_{t}^{j}}\right)=\alpha_{i}^{j}+\beta_{i}^{j}SI_{i,t}^{j}+\varepsilon_{i,t}^{j} \tag{6}$$

On the left hand side of the equation the log-return in the period from t to $t+K$ is calculated. It is the logarithm of the quotient of the price of futures contract j at point in time $t+K$ and the price of the same contract at point in time t. p_t^j is the settlement price of contract j at point in time t. The right side of the equation is the sum of the constant α_i^j, the slope coefficient β_i^j multiplied by the sentiment index of trader type i in futures market j at point in time t, and the regression error term $\varepsilon_{i,t}^j$. For the same reasons as mentioned in section 2.4 the regression is calculated for different holding periods. Again, the holding periods are 30, 60, 90, 130 and 260 trading days. Trading position time series are obtained from the CFTC's COT reports and futures prices are the continuous futures prices time series obtained from Datastream. In order to match the sample frequencies of the sentiment index and the contract prices time series, the same interpolation mechanism as outlined in section 2.4 is used.

Table 10: Regression results

PANEL A: COMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note	
30 days	β	-0.0266	(-1.78)	0.0308	(2.03)	-0.0005	(-0.03)	0.0527	(5.70)	-0.0059	(-0.82)	0.0051	(0.78)	0.0140	(2.45)	0.0000	(0.00)
	R^2	0.01	*	0.01	**	0.00		0.06	***	0.00		0.00		0.01	**	0.00	
60 days	β	-0.0152	(-0.64)	0.0618	(3.03)	-0.0342	(-1.19)	0.0848	(6.43)	0.0010	(0.10)	0.0170	(1.91)	0.0236	(3.04)	0.0018	(0.82)
	R^2	0.00		0.02	***	0.00		0.09	***	0.00		0.01		0.02	***	0.00	
90 days	β	0.0080	(0.25)	0.1088	(4.26)	-0.0846	(-2.37)	0.1015	(6.34)	0.0151	(1.11)	0.0159	(1.51)	0.0239	(2.54)	0.0057	(2.14)
	R^2	0.00		0.05	***	0.02	**	0.08	***	0.00		0.01		0.02	**	0.02	**
130 days	β	0.0503	(1.32)	0.1762	(5.82)	-0.1566	(-3.69)	0.1190	(5.81)	0.0336	(2.29)	0.0121	(0.98)	0.0227	(2.16)	0.0097	(3.06)
	R^2	0.01		0.09	***	0.04	***	0.08	***	0.01	**	0.00		0.01	**	0.03	***
260 days	β	0.1253	(2.70)	0.2468	(6.98)	-0.2744	(-4.87)	0.1628	(5.01)	-0.0208	(-1.00)	-0.0435	(-2.33)	0.0355	(2.76)	0.0220	(4.20)
	R^2	0.02	***	0.12	***	0.06	***	0.06	***	0.00		0.01	**	0.02	***	0.07	***

PANEL B: NONCOMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note	
30 days	β	0.0280	(2.09)	-0.0005	(-0.04)	0.0056	(0.30)	-0.0010	(-0.10)	0.0084	(1.15)	-0.0068	(-1.03)	-0.0152	(-2.76)	-0.0001	(-0.04)
	R^2	0.01	**	0.00		0.00		0.00		0.00		0.00		0.02	***	0.00	
60 days	β	0.0226	(1.03)	0.0073	(0.36)	0.0451	(1.68)	-0.0057	(-0.44)	0.0024	(0.24)	-0.0205	(-2.26)	-0.0248	(-3.10)	-0.0012	(-0.61)
	R^2	0.00		0.00		0.01	*	0.00		0.00		0.01	**	0.02	***	0.00	
90 days	β	0.0058	(0.19)	-0.0172	(-0.67)	0.0979	(2.94)	-0.0066	(-0.40)	-0.0068	(-0.52)	-0.0187	(-1.73)	-0.0298	(-3.09)	-0.0047	(-1.90)
	R^2	0.00		0.00		0.02	***	0.00		0.00		0.01	*	0.03	***	0.01	*
130 days	β	-0.0152	(-0.40)	-0.0659	(-2.18)	0.1770	(4.45)	-0.0106	(-0.54)	-0.0211	(-1.51)	-0.0202	(-1.57)	-0.0298	(-2.83)	-0.0115	(-3.90)
	R^2	0.00		0.01	**	0.05	***	0.00		0.00		0.01		0.02	***	0.04	***
260 days	β	-0.0946	(-1.81)	-0.1253	(-3.42)	0.3369	(6.38)	0.0122	(0.43)	0.0515	(2.58)	0.0329	(1.71)	-0.0580	(-4.46)	-0.0280	(-5.60)
	R^2	0.01	*	0.03	***	0.09	***	0.00		0.02	**	0.01	*	0.05	***	0.11	***

PANEL C: NONREPORTABLES

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note	
30 days	β	-0.0181	(-1.15)	-0.0520	(-3.48)	0.0098	(0.44)	-0.0533	(-6.25)	0.0018	(0.25)	-0.0060	(-0.90)	-0.0096	(-1.64)	-0.0008	(-0.57)
	R^2	0.00		0.03	***	0.00		0.07	***	0.00		0.00		0.01		0.00	
60 days	β	-0.0281	(-1.17)	-0.1218	(-6.42)	0.0421	(1.28)	-0.0866	(-7.30)	-0.0035	(-0.33)	-0.0161	(-1.69)	-0.0202	(-2.67)	-0.0035	(-1.73)
	R^2	0.00		0.11	***	0.00		0.10	***	0.00		0.01	*	0.01	***	0.01	*
90 days	β	-0.0305	(-1.08)	-0.1621	(-7.41)	0.0941	(2.36)	-0.1120	(-6.64)	-0.0217	(-1.58)	-0.0159	(-1.39)	-0.0257	(-2.71)	-0.0064	(-2.47)
	R^2	0.00		0.13	***	0.02	**	0.11	***	0.01		0.01		0.02	***	0.02	**
130 days	β	-0.0535	(-1.65)	-0.2116	(-8.21)	0.1516	(3.22)	-0.1354	(-6.61)	-0.0402	(-2.64)	-0.0068	(-0.54)	-0.0302	(-2.68)	-0.0077	(-2.67)
	R^2	0.01	*	0.16	***	0.03	***	0.10	***	0.02	***	0.00		0.02	***	0.02	***
260 days	β	0.0025	(0.06)	-0.3277	(-10.16)	0.1944	(3.05)	-0.2270	(-7.19)	-0.0142	(-0.69)	0.0623	(3.12)	-0.0082	(-0.61)	-0.0173	(-3.92)
	R^2	0.00		0.22	***	0.02	***	0.11	***	0.00		0.03	***	0.00		0.04	***

Regression equation: (6). Data sources: CFTC COT reports (trading positions), Datastream (contract prices). Sample: 01/01/1995-12/31/2006. Newey-West (1987) adjusted t-statistics under the null hypothesis that $\beta_i^j = 0$ are displayed in parentheses. * , ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. R^2 is the regression model's unadjusted coefficient of determination.

Table 10 displays the results of the regressions. Panel A contains the regression results for the Commercials' sentiment index, Panel B those for the Noncommercials and Panel C those for the Nonreportables. The results for the different holding periods are displayed in rows among one another. For each regression the slope coefficient β, the R^2 coefficient of determination and the Newey-West (1987) adjusted t-Statistics for the null hypothesis $\beta_i^j = 0$ (in parentheses) are reported. A positive β would indicate that a high investor sentiment goes along with high returns in the subsequent K trading days while a negative β would mean the opposite. As aforementioned, β slope coefficients in this regression framework can be compared among different futures contracts. Consider, for example, the slope coefficient for the Wheat contract and the Noncommercials' sentiment index with a holding period of 260 days. The value of 0.2468 indicates that an increase of investor sentiment by 0.1 or 10% goes along with an average increase of returns in the Wheat contract of 2.468% during the following 260 trading days.

Compared to section 2.4 the R^2 coefficients of determination in this regression framework are noticeably smaller. This finding is rather unsurprising, however, because the former regression equation related movements in futures prices to changes in net positions that happened at the same time. Equation (6), in contrary, has a forecasting component. Despite having generally smaller R^2 values, several coefficients of determination are remarkably high, considering that this is a forecasting regression framework. For example, R^2 for the Noncommercials' sentiment index in the S&P 500 contract are in the range between 5% and 10%. For the Nonreportables' sentiment index, particularly high R^2 can be witnessed for the Wheat and the S&P 500 contract. In one occasion, a value of over 20% is achieved. Results show that statistically significant t-statistics can be found across all contracts analyzed. In many cases results are significant even at the 1% level. Aiming to forecast returns in futures markets, these results are encouraging, at first glance: Evidence suggests that there is a relation between current sentiment indices and futures returns in subsequent periods in a notable proportion of the total 150 results. For the S&P 500 future the obtained R^2 values are of a similar magnitude as those reported in Wang (2003). In Wang (2001) no R^2 values have been stated, so the values for the Corn and Wheat contracts can not be compared with the results in that paper.

The main finding is that slope coefficients differ materially among futures contracts. From the Commercials' sentiment indices, for example, 4 contracts had positive slope coefficients, 2 had negative and for the remaining 4 contracts the algebraic sign was dependent on the holding period. The same mixed picture can be observed for the Noncommercials' and the Nonreportables' sentiment indices. This means that the findings of Wang (2001, 2003) who reported positive negative slope coefficients for large hedgers and positive slope coefficients for large speculators without any exceptions for all contracts he analyzed can *not* be generalized. In the majority of cases, the algebraic signs of the slope coefficients for the Commercials were the opposite of those for the Noncommercials. This finding is not surprising, considering the strong negative correlation shown in Table 9. In summary, slope coefficients depend on a) the contract under investigation, b) on the type of trader and c) on the holding period. It can be noticed that slope coefficients are inconsistent even among contracts from the same asset category. The slope coefficients for Noncommercials for the Gold and Silver contracts, for instance, are diametrically opposed. It shall also be noted that in many cases, algebraic signs of slope coefficients are unstable with respect to the selected holding period. Only for 4 out of 10 contracts algebraic signs of the slope coefficients were independent of holding periods. Observed absolute values for β were especially high for the Light Sweet Crude Oil future and hardly different from zero for the Treasury Note future.

Obtained results for the Light Sweet Crude Oil future coincide exactly with those reported by Sanders, Boris & Manfredo (2004). The results for the Corn, Wheat and S&P 500 futures, however, differ materially from those reported in Wang (2001) and Wang (2003). In the latter paper the effects of investor sentiment on returns in the S&P 500 future were investigated. In the context of the same regression equation as applied here, the author reported negative slope coefficients for the large hedger sentiment index and positive slope coefficients for the large speculator index. The results in Table 10 show exactly the opposite pattern, however. Explaining these differences is rather simple, however: Wang (2003) used detrended return time series instead of realized return time series. The detrending method is described as follows (Wang, 2003): „To assess the return predictability of sentiment, a return series is constructed by subtracting the 12-week moving average from the raw return series. This ‚detrending' helps to rule out the possibility that the timing signal provided by sentiment coincides with a sustained bull (bear) market." The case for using such detrended returns seems to be rather weak. First, by means of the sentiment index, investors would prefer to forecast real returns instead of detrended returns. Second, the benefit of using the sentiment index would obviously be larger if it was able to predict exactly those bull and bear markets mentioned. Therefore, it has been decided not to adopt Wang's methodology of using detrended return series. In Wang (2001) six agricultural futures contracts were analyzed. Among those were also the Corn and Wheat futures. The author's findings were the same as those for the S&P 500 contract. Table 10, in comparison, shows rather mixed results for Corn and Wheat. Here, the reason for the differences is not so obvious, because Wang (2001) refrained from detrending the return series in this study. Possible explanations for the dissenting results would be different holding periods and different samples. Wang (2001) only reported results for holding periods of 8 weeks, which usually equals 40 trading days. The sample in Wang's study was 01/1993 to 03/2000.

In order to test whether slope coefficients are stable within time, a test of regression equation (6) on three sub-sample periods is proposed. If it was found that the slope coefficients are not stable among sub-samples, this could explain the differences to Wang (2001). Second, a test of sub-samples can be used to confirm or disprove the robustness of the obtained results. If the results for all sub-samples are approximately the same, this finding would emphasize the robustness of the results. Robust results would in turn encourage the use of the sentiment index for further forecasts.

Table 10 reported the results of regression equation (6) for the full sample period (01/01/1995 – 12/31/2006). Now the full sample of 12 years is split into 3 sub-samples with a length of 4 years each. Then, regression equation (6) is calculated for each of the sub-samples. The tables with the regression results for the 3 sub-samples can be found in Appendix A. In the main part of the thesis only a summary of the results is presented.

Table 11: Comparison of sub-samples

PANEL A: COMMERCIALS

Sample	Period	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Sub-sample 1	01/01/1995 - 12/31/1998	−−	−−	−	++	+	+	++	+	+	++
Sub-sample 2	01/01/1999 - 12/31/2002	++	++	−−	++	+	−	−	++	−−	++
Sub-sample 3	01/01/2003 - 12/31/2006	+	++	+	++	−−	++	++	−	++	++
Full sample	01/01/1995 - 12/31/2006	+	++	−−	++	+	+	++	++	−−	+

PANEL B: NONCOMMERCIALS

Sample	Period	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Sub-sample 1	01/01/1995 - 12/31/1998	++	++	−	−−	−	−−	−−	−	−	−−
Sub-sample 2	01/01/1999 - 12/31/2002	−−	−−	++	−−	−	−	+	−−	+	−−
Sub-sample 3	01/01/2003 - 12/31/2006	−	−−	−	−−	++	−	−−	+	−	−−
Full sample	01/01/1995 - 12/31/2006	+	−	++	−	+	−	−−	−−	++	−−

PANEL C: NONREPORTABLES

Sample	Period	Corn	Wheat	Oil	SP500	JPY	CHF	Bond	Note	Gold	Silver
Sub-sample 1	01/01/1995 - 12/31/1998	−	−−	+	−−	−−	−	−−	−−	−−	−−
Sub-sample 2	01/01/1999 - 12/31/2002	−	−	++	−−	−	−	−−	−−	++	+
Sub-sample 3	01/01/2003 - 12/31/2006	−	−	−−	−	−−	−−	−−	+	−−	−
Full sample	01/01/1995 - 12/31/2006	−	−−	++	−−	−	−	−−	−−	+	+

Regression equation: (6). Data sources: CFTC COT reports (trading positions), Datastream (contract prices). Samples as stated above. Explanation of symbols: ++: Slope coefficient has been positive for all 5 holding periods. +: Slope coefficient has been positive in the majority (3 or 4) of holding periods. --: Slope coefficient has been negative for all 5 holding periods. -: Slope coefficient has been negative in the majority (3 or 4) of holding periods. Shaded areas signify that the algebraic sign of the slope coefficient has remained consistent at least for the majority of the 5 holding periods.

Table 11 summarizes the regression results for the full sample (see Table 10) and the 3 sub-samples (see Appendix A). Tabular values symbolize the algebraic signs of the slope coefficients. ++ means that the slope coefficient has been positive for all 5 holding periods investigated. + signifies positive slope coefficients in the majority of the 5 holding periods. Thus, it stands for 3 or 4 positive slope coefficients out of 5. The meanings for the -- and - symbols are analogous, but they represent negative slope coefficients. Fields where results have been consistent among all samples have been shaded. Therefore, the gray shade signifies that the majority of algebraic signs have remained constant over all sample periods.

Strikingly, slope coefficients are consistent in only 11 out of 30 cases. The S&P 500 future is the only contract where the algebraic signs of β remained constant for all three sentiment indices. For the Silver contract, consistent results for the Commercials' and the Noncommercials' but not for the Nonreportables' sentiment indices were found. The most robust indicator has been the Nonreportables' sentiment index. For 6 out of 10 contracts, slope coefficients had negative algebraic sign across all samples. Therefore one pattern seems to apply very often, even if market conditions change: When small traders are getting very bullish, a market downturn is nigh. In this sense, results of older studies like Stewart (1949) and Babcock (1989) can be confirmed. Table 11 provides some very interesting information with regards to the two agricultural contracts. The slope coefficients for both, Corn and Wheat, made a u-turn from the first to the second sub-sample: While having been negative for the Commercials' sentiment index and positive for the Noncommercials' in the first sub-sample, the slope coefficient have been exactly the opposite in the second and third sub-sample. Note also that the results for Corn and Wheat during the 4 years have been the opposite of the full sample results[14]. This discovery explains why the regressions for the full sample have shown the opposite of Wang's (2001) results. Sub-sample 1 is the only sample that is fully within Wang's sample which was from 01/1993 to 03/2000. And the results for this very sub-sample are exactly the same as those reported in Wang (2001).

It is also noteworthy that slope coefficients were unstable for several other contracts. There is no unambiguous explanation why high speculator sentiment would signalize an upcoming bull market during the first 4 years but indicate the opposite during the next 4 years. Of course, it could be argued that the link between the sentiment index and futures returns is just a spurious correlation. Findings from section 2.4 would strongly contradict to this notion, however, because strong relations between trading positions and futures prices have been proven. The sentiment index, in turn, is calculated from exactly these trading positions. Another explanation for the observed phenomenon could be changes in the market structure like hedging pressure effects changing over time. This explanation would be supported by the results that can be found in Appendix A. Interestingly, R^2 coefficients of determination are much higher for the sub-sample regressions as compared to the regressions for the full sample. Some sub-sample regressions even yield R^2 values of around 50%. This would support the notion of changes in the market structure.

4 Sentiment-based trading strategy

4.1 Description

In this chapter it shall be analyzed what returns an investor with a trading strategy that based on the proposed sentiment index would have realized. Therefore, a simple trading strategy is proposed: The sentiment index can be interpreted as a measure of traders' confidence. Consequently, high levels of confidence can be interpreted as a buy signal while low levels of confidence can be interpreted as a sell signal. Up to now, there is no literature on sentiment-based trading strategies in futures markets, so there is no benchmark strategy that could be followed. Therefore a new trading strategy has been developed: If the sentiment index reaches or exceeds a predefined threshold (TH), a buy signal is generated. If, on the other hand, the sentiment index reaches or falls below a value of one minus the predefined threshold, a sell signal would be generated. After a buy or sell signal has been generated, the entered position is held for a predefined number (K) of trading days. It is possible that multiple positions are held simultaneously. Consider, for instance, a situation where the sentiment index first exceeds the threshold level and

[14] With the exception of the Corn sentiment index of Noncommercials and the sentiment indices for Nonreportables, of course.

then falls below the level of $(1-TH)$ before K trading days have elapsed. In such a case the trader would hold both, a long and a short position, as a result. In formal notation the trading strategy can be written as

$$SI_{i,t}^{j}\begin{cases} SI_{i,t}^{j} \geq TH \begin{cases} SI_{i,t-1}^{j} < TH \rightarrow \text{go long 1 contract} \\ SI_{i,t-1}^{j} \geq TH \rightarrow \text{do nothing} \end{cases} \\ SI_{i,t}^{j} < TH \wedge SI_{i,t}^{j} > (1-TH) \rightarrow \text{do nothing} \\ SI_{i,t}^{j} \leq (1-TH) \begin{cases} SI_{i,t-1}^{j} \leq (1-TH) \rightarrow \text{do nothing} \\ SI_{i,t-1}^{j} > (1-TH) \rightarrow \text{go short 1 contract} \end{cases} \end{cases} \tag{7}$$

where $SI_{i,t}^{j}$ is the sentiment index for trader type i in futures market j at point in time t and TH is the predefined threshold level. It is differentiated between three cases: In the first case, the sentiment index is at or above the threshold level. A long position will only be entered, however, if the sentiment index surpassed the index at the current point in time t. Nothing happens if the sentiment index has been at or above the threshold level at the preceding point in time $t-1$. The second case consists of the sentiment index being below the threshold level and above one minus the threshold level. No trading signal is generated because investor sentiment is on a level that suggests neither excessively large nor weak confidence. A short position will be entered, however, if the sentiment index reaches or falls below the border of $(1-TH)$, given that the index has not been there one trading day ago.

The selection of values for the threshold level TH and the holding period K is completely arbitrary of course. Thus, a sensitivity analysis is part of this chapter. The analysis will show how the returns of the trading strategy react to changes in TH and K.

Usually, three days are passing between the "as of" and the release date of COT reports. Consequently, sentiment indices are updated with a delay of three days in practice. In order to make the trading strategy more realistic this fact has been incorporated when programming the strategy. Transaction costs, however, have not been included because they were too small to have any noteworthy effects on trading performances[15].

4.2 Performance of trading signals

The above-described trading strategy has been implemented for the sentiment indices of all three types of traders and for all 10 contracts analyzed. It has been decided to set $TH = 1$. This means that a buy signal is generated when the sentiment index reaches the value of 1 whereas a sell signal is generated when the index reaches $TH - 1 = 0$. Like in previous analyses, the selected holding periods K are 30, 60, 90, 130 and 260 trading days.

[15] As compared to other asset classes like equities, transaction fees in futures markets are very small (in relation to the large contract volumes). See for example Interactive Brokers (2007) for quotes on futures trading commission fees.

Table 12: Performance of the trading strategy

PANEL A: COMMERCIALS, SENTIMENT INDEX THRESHOLD = 1

HP	Variable		Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	n	*Hit ratio*	21	*52%*	18	*78%*	14	*43%*	15	*67%*	19	42%	15	*53%*	18	*61%*	23	*35%*	14	*57%*	25	*60%*
	Mean	*St. dev.*	19.05%	*25%*	50.68%	*26%*	-22.53%	*30%*	21.00%	*15%*	-7.57%	11%	-3.24%	*11%*	7.66%	*7%*	-2.40%	*3%*	6.99%	*16%*	24.17%	*23%*
	t-Stat	*Sharpe r.*	3.49	*0.76*	8.27	*1.95*	-2.81	*-0.75*	5.42	*1.40*	-3.00	*-0.69*	-1.14	*-0.29*	4.64	*1.09*	-3.84	*-0.80*	1.63	*0.44*	5.25	*1.05*
60 days	n	*Hit ratio*	21	*57%*	18	*67%*	14	*21%*	15	*67%*	19	32%	15	*53%*	18	*50%*	23	*43%*	14	*43%*	25	*60%*
	Mean	*St. dev.*	7.30%	*23%*	21.52%	*26%*	-21.26%	*33%*	11.46%	*13%*	-5.47%	10%	5.55%	*8%*	5.07%	*8%*	0.07%	*2%*	-3.31%	*11%*	12.77%	*22%*
	t-Stat	*Sharpe r.*	1.45	*0.32*	3.51	*0.83*	-2.41	*-0.64*	3.41	*0.88*	-2.38	*-0.55*	2.69	*0.69*	2.69	*0.63*	0.17	*0.04*	-1.13	*-0.30*	2.90	*0.58*
90 days	n	*Hit ratio*	21	*57%*	18	*78%*	14	*36%*	15	*87%*	19	47%	15	*53%*	18	*39%*	23	*48%*	14	*43%*	25	*48%*
	Mean	*St. dev.*	10.12%	*27%*	27.02%	*20%*	-20.32%	*37%*	17.97%	*10%*	-2.92%	14%	4.45%	*9%*	1.27%	*8%*	0.78%	*2%*	-8.48%	*10%*	2.66%	*20%*
	t-Stat	*Sharpe r.*	1.72	*0.37*	5.73	*1.35*	-2.05	*-0.55*	6.96	*1.80*	-0.91	*-0.21*	1.91	*0.49*	0.67	*0.16*	1.87	*0.39*	-3.17	*-0.85*	0.67	*0.13*
130 days	n	*Hit ratio*	21	*86%*	18	*83%*	14	*29%*	15	*87%*	19	53%	15	*67%*	18	*44%*	23	*57%*	14	*50%*	25	*56%*
	Mean	*St. dev.*	20.63%	*23%*	29.39%	*24%*	-27.32%	*37%*	16.96%	*11%*	2.96%	10%	5.74%	*8%*	-0.57%	*7%*	1.42%	*2%*	-5.16%	*12%*	6.91%	*21%*
	t-Stat	*Sharpe r.*	4.11	*0.90*	5.20	*1.22*	-2.76	*-0.74*	5.97	*1.54*	1.29	*0.30*	2.78	*0.72*	-0.35	*-0.08*	3.41	*0.71*	-1.61	*-0.43*	1.65	*0.33*
260 days	n	*Hit ratio*	21	*67%*	18	*89%*	14	*29%*	15	*93%*	19	21%	15	*73%*	18	*56%*	23	*65%*	14	*14%*	25	*64%*
	Mean	*St. dev.*	2.22%	*28%*	16.70%	*18%*	-25.63%	*39%*	15.06%	*12%*	-1.02%	8%	2.64%	*8%*	0.84%	*6%*	0.92%	*3%*	-8.57%	*10%*	3.49%	*16%*
	t-Stat	*Sharpe r.*	0.36	*0.08*	3.94	*0.93*	-2.46	*-0.66*	4.86	*1.26*	-0.56	*-0.13*	1.28	*0.33*	0.59	*0.14*	1.47	*0.31*	-3.21	*-0.86*	1.09	*0.22*

PANEL B: NONCOMMERCIALS, SENTIMENT INDEX THRESHOLD = 1

HP	Variable		Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	n	*Hit ratio*	18	*50%*	22	*41%*	20	*50%*	22	*64%*	22	50%	17	*53%*	27	*48%*	21	*48%*	15	*53%*	18	*56%*
	Mean	*St. dev.*	-14.06%	*24%*	-5.15%	*30%*	7.32%	*28%*	7.46%	*16%*	3.62%	11%	2.98%	*11%*	-3.37%	*7%*	-0.94%	*2%*	-8.24%	*17%*	-16.95%	*23%*
	t-Stat	*Sharpe r.*	-2.49	*-0.59*	-0.81	*-0.17*	1.17	*0.26*	2.19	*0.47*	1.54	*0.33*	1.12	*0.27*	-2.50	*-0.48*	-2.15	*-0.47*	-1.88	*-0.48*	-3.13	*-0.74*
60 days	n	*Hit ratio*	18	*44%*	22	*55%*	20	*75%*	22	*55%*	22	55%	17	*47%*	27	*56%*	21	*43%*	15	*47%*	18	*44%*
	Mean	*St. dev.*	-0.88%	*23%*	0.32%	*27%*	24.40%	*32%*	-1.57%	*14%*	2.62%	9%	-1.79%	*8%*	-3.13%	*8%*	-1.20%	*2%*	3.47%	*12%*	-4.24%	*26%*
	t-Stat	*Sharpe r.*	-0.16	*-0.04*	0.06	*0.01*	3.41	*0.76*	-0.53	*-0.11*	1.37	*0.29*	-0.92	*-0.22*	-2.03	*-0.39*	-2.75	*-0.60*	1.12	*0.29*	-0.69	*-0.16*
90 days	n	*Hit ratio*	18	*44%*	22	*50%*	20	*70%*	22	*55%*	22	50%	17	*65%*	27	*44%*	21	*29%*	15	*60%*	18	*50%*
	Mean	*St. dev.*	-5.68%	*26%*	-7.97%	*29%*	21.45%	*30%*	0.14%	*11%*	0.73%	12%	0.45%	*8%*	-3.74%	*9%*	-1.29%	*2%*	13.24%	*13%*	-5.81%	*24%*
	t-Stat	*Sharpe r.*	-0.93	*-0.22*	-1.29	*-0.27*	3.20	*0.72*	0.06	*0.01*	0.29	*0.06*	0.23	*0.06*	-2.16	*-0.42*	-2.96	*-0.65*	3.94	*1.02*	-1.03	*-0.24*
130 days	n	*Hit ratio*	18	*22%*	22	*24%*	20	*75%*	22	*45%*	22	41%	17	*41%*	27	*44%*	21	*19%*	15	*53%*	18	*44%*
	Mean	*St. dev.*	-12.86%	*25%*	-14.64%	*29%*	27.28%	*31%*	-4.04%	*11%*	-4.78%	9%	-4.42%	*9%*	-2.70%	*8%*	-1.98%	*2%*	9.83%	*14%*	-6.10%	*24%*
	t-Stat	*Sharpe r.*	-2.18	*-0.51*	-2.37	*-0.50*	3.94	*0.88*	-1.72	*-0.37*	-2.49	*-0.53*	-2.02	*-0.49*	-1.75	*-0.34*	-4.54	*-0.99*	2.72	*0.70*	-1.08	*-0.25*
260 days	n	*Hit ratio*	18	*22%*	22	*36%*	20	*85%*	22	*45%*	22	68%	17	*41%*	27	*44%*	21	*10%*	15	*87%*	18	*56%*
	Mean	*St. dev.*	3.60%	*32%*	-3.75%	*21%*	26.55%	*30%*	0.26%	*14%*	0.47%	8%	-0.65%	*8%*	-2.33%	*8%*	-1.51%	*2%*	11.52%	*13%*	0.13%	*15%*
	t-Stat	*Sharpe r.*	0.48	*0.11*	-0.84	*-0.18*	3.96	*0.89*	0.09	*0.02*	0.28	*0.06*	-0.34	*-0.08*	-1.51	*-0.29*	-3.46	*-0.76*	3.43	*0.89*	0.04	*0.01*

PANEL C: NONREPORTABLES, SENTIMENT INDEX THRESHOLD = 1

HP	Variable		Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	n	*Hit ratio*	15	*33%*	22	*50%*	10	*50%*	18	*33%*	11	55%	16	*44%*	17	*41%*	19	*63%*	10	*50%*	21	*29%*
	Mean	*St. dev.*	-13.49%	*32%*	-6.45%	*26%*	-3.98%	*35%*	-22.51%	*15%*	1.46%	10%	0.37%	*13%*	-0.87%	*8%*	2.15%	*3%*	-9.48%	*16%*	-14.15%	*33%*
	t-Stat	*Sharpe r.*	-1.63	*-0.42*	-1.16	*-0.25*	-0.36	*-0.11*	-6.37	*-1.50*	0.48	*0.15*	0.11	*0.03*	-0.45	*-0.11*	3.12	*0.72*	-1.87	*-0.59*	-1.96	*-0.43*
60 days	n	*Hit ratio*	15	*33%*	22	*27%*	10	*30%*	18	*33%*	11	64%	16	*38%*	17	*53%*	19	*58%*	10	*30%*	21	*33%*
	Mean	*St. dev.*	-3.48%	*31%*	-26.71%	*27%*	-16.56%	*38%*	-16.29%	*15%*	3.51%	9%	-5.07%	*8%*	-2.15%	*6%*	-1.03%	*3%*	-11.73%	*13%*	-17.93%	*23%*
	t-Stat	*Sharpe r.*	-0.43	*-0.11*	-4.64	*-0.99*	-1.38	*-0.44*	-4.61	*-1.09*	1.29	*0.39*	-2.54	*-0.63*	-1.48	*-0.36*	-1.50	*-0.34*	-2.85	*-0.90*	-3.57	*-0.78*
90 days	n	*Hit ratio*	15	*33%*	22	*18%*	10	*70%*	18	*22%*	11	27%	16	*38%*	17	*47%*	19	*58%*	10	*60%*	21	*43%*
	Mean	*St. dev.*	-11.15%	*28%*	-29.09%	*23%*	23.22%	*38%*	-23.57%	*18%*	-9.36%	13%	-5.23%	*9%*	-1.10%	*6%*	-1.11%	*2%*	1.91%	*16%*	-4.15%	*24%*
	t-Stat	*Sharpe r.*	-1.54	*-0.40*	-5.93	*-1.26*	1.93	*0.61*	-5.56	*-1.31*	-2.39	*-0.72*	-2.32	*-0.58*	-0.76	*-0.18*	-2.42	*-0.56*	0.38	*0.12*	-0.79	*-0.17*
130 days	n	*Hit ratio*	15	*47%*	22	*27%*	10	*70%*	18	*22%*	11	18%	16	*38%*	17	*59%*	19	*47%*	10	*60%*	21	*48%*
	Mean	*St. dev.*	-9.91%	*31%*	-25.92%	*24%*	30.77%	*38%*	-18.02%	*17%*	-9.04%	11%	-3.10%	*9%*	0.75%	*9%*	-1.16%	*2%*	-3.88%	*18%*	0.10%	*24%*
	t-Stat	*Sharpe r.*	-1.24	*-0.32*	-5.07	*-1.08*	2.56	*0.81*	-4.50	*-1.06*	-2.73	*-0.82*	-1.38	*-0.34*	0.34	*0.08*	-2.53	*-0.58*	-0.68	*-0.22*	0.02	*0.00*
260 days	n	*Hit ratio*	15	*47%*	22	*23%*	10	*60%*	18	*22%*	11	27%	16	*31%*	17	*65%*	19	*37%*	10	*80%*	21	*43%*
	Mean	*St. dev.*	-2.80%	*22%*	-16.96%	*21%*	19.52%	*50%*	-12.39%	*19%*	-6.56%	8%	0.82%	*11%*	1.27%	*6%*	-0.83%	*2%*	1.87%	*25%*	5.41%	*15%*
	t-Stat	*Sharpe r.*	-0.49	*-0.13*	-3.79	*-0.81*	1.23	*0.39*	-2.77	*-0.65*	-2.72	*-0.82*	0.30	*0.07*	0.87	*0.21*	-1.81	*-0.42*	0.24	*0.07*	1.65	*0.36*

Data sources: CFTC COT reports (trading positions), Datastream (contract prices). Sample: 01/01/1995 -12/31/2006. n denotes the sum of buy and sell signals generated. The hit ratio is the proportion of trading signals that yielded a positive return. Mean is the annualized average return generated by a trading signal. St. dev. is the annualized standard deviation of the returns of the n trading signals. Reported t-statistics are under the null hypothesis $H_0 : Mean = 0$. The Sharpe (1966, 1994) ratio is calculated as the quotient of the mean and the standard deviation.

Table 12 shows the results of the trading strategy. Several measurements of the trading performance are indicated: n is the number of (buy and sell) signals generated by the trading strategy. The hit ratio is the percentage of trading signals that led to a positive return. Mean is the annualized average return of the trading signals generated by the strategy. In order to ensure the comparability of values for different holding periods, reported standard deviations have been annualized as well. t-Statistics are under the null hypothesis that the annualized mean return is zero. The reported Sharpe (1966, 1994) ratios serve as a measurement of risk-adjusted returns. When calculating the Sharpe Ratio the risk-free return has been set to zero because – due to daily marking to market – trading in futures markets does not require any capital expenditures (apart from margin requirements that are small relative to the volume of the futures contracts). No capital expenditures imply that there are no risk-free returns that the trader would miss out on. The sample period is from 01/01/1995 to 12/31/2006. Note that the sentiment indices could not be calculated as of 1992 because they require three years "lead time" (confer section 3.1). Panel A shows the results for the Commercials' sentiment index, Panel B those for the Noncommercials' and Panel C those for the Nonreportables'.

In Panel A the trading strategy realized high mean returns in the Corn, Wheat, S&P 500 and the Silver contract. Evidence suggests that large hedging sentiment is a good buying indicator in the two agricultural markets analyzed. For the sentiment index of speculative traders, the results for the Light Sweet Crude Oil contract were excellent. In those cases the t-statistics were mostly significant[16]. The sentiment of nonreportable traders, in contrary, seems to be a bad adviser: In 36 out 50 cases one would have made a loss using the Nonreportables' sentiment index for trading decisions. It seems like this sentiment index would only be useful as a contrary indicator[17]. Once again it is shown that small traders in general seem to have unfavorable market timing skills. High sentiment of hedging traders in the Light Sweet Crude Oil contract has also lead to significant losses. The same finding applies to Silver and Corn contracts the Commercials' sentiment index. In summary, obtained results confirm the outcome of the forecasting regression framework (confer Table 10): Generally, returns of the trading strategy have been high where the regression framework found positive slope coefficients. Areas where significantly positive returns are achieved are in most cases found to be accompanied by high hit ratios. Quite often, hit ratios of over two thirds have been achieved. In some instances, hit ratios even exceeded 80%. Sharpe Ratios, in turn, surpassed values of 1 only in exceptional cases. This demonstrates that positive returns were generally accompanied by high standard deviations. Therefore, the sentiment-based trading strategy does not seem to be particularly attractive from a perspective of risk-adjusted returns.

4.3 Sensitivity analysis

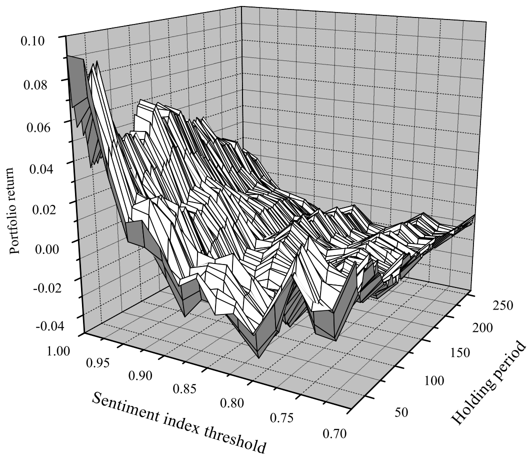
In the previous analyses a threshold level of $TH = 1$ with $K = \{30,\ 60, 90, 130, 260\}$ has been used. Now in this section it is investigated how average returns depend on the selection of the two arbitrary variables TH and K. The objective is to detect some patterns that are preferably universally valid – regardless of the contract analyzed. Consequently, the following analysis will be conducted on a portfolio level and not on the level of single futures contracts. The portfolio consists of the 10 analyzed futures contracts with a weight of 10% each. Thus, the average annualized return for all 10 contracts is calculated.

[16] Note that due to lack of space only t-statistics but not the corresponding significance levels have been indicated.

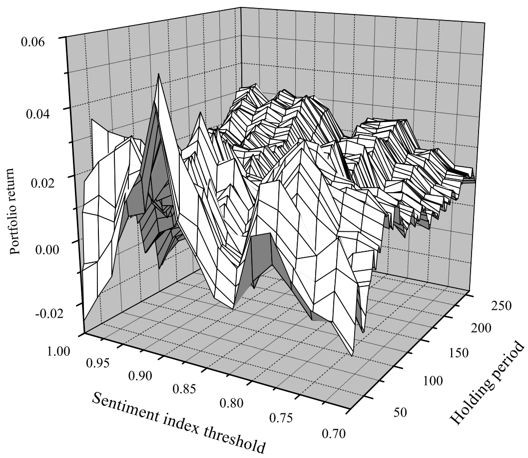
[17] That is, interpreting high sentiment as selling signal and vice versa.

Figure 5: Sensitivity analysis

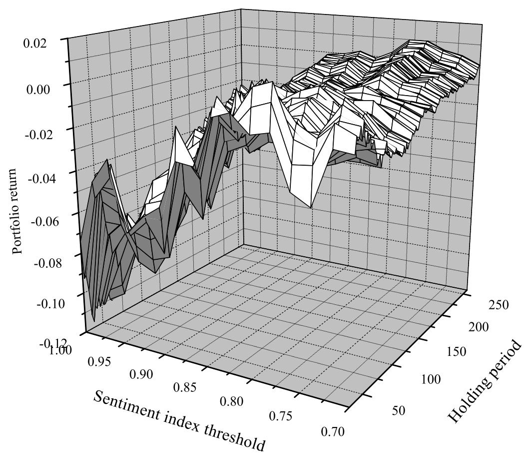
Panel A: Commercials



Panel B: Noncommercials



Panel C: Nonreportables



Data sources: CFTC COT reports (trading positions), Datastream (contract prices). Sample: 01/01/1995 -12/31/2006.

Figure 5 shows the results for the three types of traders. The x-axis of the charts shows the sentiment index threshold, the y-axis represents the holding period and the z-axis signifies the average annual return in dependence of the other two variables. The underlying data for the three charts can be found in Appendix B.

Inspecting the chart for the Commercials' sentiment index (Panel A), it becomes apparent that higher returns could be achieved when the threshold for buying signals was at the maximum (and therefore the threshold for selling signals at the minimum) of the sentiment index. In the observation period a reduction of the threshold level to a value below 1 has been counterproductive. Setting $TH > 0.90$ dramatically reduced the probability of a positive outcome. Below this level, the average return was almost constantly in negative territory, regardless of the holding period. Second, the chart suggests that annualized returns are slightly higher for shorter holding periods. This notion intuitively makes sense: In the days following the triggered trading signal the effects on returns should be more perceptible than in more distant periods. On an annualized basis, returns for shorter holding periods therefore should be higher. The chart for the Noncommercials does not exhibit clear patterns. It can be concluded, however, that average annualized returns have been in positive territory in the vast majority of cases. Exceptions were, amongst others, combinations of high threshold levels and short holding periods. Panel C, which displays the outcome for nonreportable traders, provides some distinct patterns. Obviously, it has been very unlikely that a trading strategy based on the sentiment of small traders would have yielded a positive return. It is therefore recommended to use this index as a contrary and not as a continuation indicator. The biggest losses were realized when threshold levels were set particularly high. In these cases, the average annualized return of a trading signal generated by this sentiment index was around -10%.

4.4 Benchmarking

To conclude this chapter, the performance of the sentiment-based trading strategy will be compared with a buy and hold strategy in futures contracts and with alternative asset classes.

Table 13: Benchmarking

Benchmark		Mean annualized return	Annualized st. dev.	Sharpe Ratio*
Sentiment-based trading strategy (Commercials)	TH=1, K=30	9.05%	19.21%	0.47
Sentiment-based trading strategy (Noncommercials)	TH=1, K=30	-2.59%	18.44%	-0.14
Sentiment-based trading strategy (Nonreportables)	TH=1, K=30	-7.44%	21.56%	-0.35
Buy and hold (equally-weighted futures portfolio)		3.94%	8.56%	0.46
Dow Jones Industrial Average		10.31%	16.99%	0.43
S&P 500		9.86%	17.40%	0.40
Dow Jones AIG Commodity Index		4.81%	13.79%	0.13

* Risk-free asset: Annualized average yield of a 30 days Treasury Bill = 2.95%

Data sources: CFTC COT reports (trading positions), Datastream (futures prices), Bloomberg (Dow Jones Industrial Average, S&P 500, Dow Jones AIG Commodity Index). Sample: 01/01/1995 – 12/31/2006.

Table 13 shows the mean annualized returns, the annualized standard deviations as a measurement of the volatility and the Sharpe (1966, 1994) Ratios for the benchmarked assets. For the sentiment-based trading strategy, values for the threshold level TH and the holding period K had to be selected first. It has been decided to leave the threshold level at its initial level of 1. In addition, the shortest holding period of the sensitivity analysis, namely 30 trading days, has been selected. The performance measurements for the sentiment-based trading strategies for all three types of traders are indicated. When calculating the Sharpe Ratios, it has been assumed that investments in futures do not require any capital expenses. Thus, the risk-free rate has been set to zero for the sentiment-based trading strategies and the futures buy and hold strategy. Investments in the Dow Jones Industrial Average, the S&P 500 and the Dow Jones AIG Commodity Index usually require capital expenses, on the other hand[18]. Therefore, the risk-free rate has been deducted from their annual returns. The annualized average yield of the 30 days Treasury Bill has been selected to represent the risk-free rate. Futures price time series have been obtained from Datastream, while prices for the other assets have been obtained from Bloomberg. Transaction costs have been disregarded throughout all calculations.

Results show that the trading strategy that based on hedger's sentiment yielded positive returns while the returns for Noncommercials and Nonreportables were in negative territory. A buy and hold strategy of an equally-weighted portfolio that consisted of the 10 futures contracts investigated would have yielded an annual return of 3.94% and a volatility of 8.56%. The low volatility is the result of diversification effects in the portfolio. Both, the Dow Jones Industrial Average and the S&P 500 Index, yielded roughly 10% per annum. The Dow Jones AIG Commodity Index, on the other hand, featured a lower return and a lower risk.

Comparing the performance measurements of the sentiment-based trading strategies with those of other investment or trading opportunities, it becomes clear that it is an underperformer: Fluctuations in returns are rather high and only one of the three strategies yielded a positive return. Of course, there are reasons that can explain this underperformance: The overall return of the sentiment-based trading strategy in this example is based on the returns of the 10 individual futures contracts. Table 13 shows how well the sentiment-based trading strategy has done with regards to the single futures contracts. Consider, for example the results for the Commercials in Panel A: It can be seen that the trading strategy produced stellar results in the two agricultural contracts. These gains, however, were at least partly offset by substantial losses in the Light Sweet Crude Oil and the Gold contracts. In total, the performance was negatively affected by some contracts that consistently generated wrong trading signals. If the performance of the sentiment-based trading strategy for some of the successful contracts would be compared to the benchmark values then the results would be completely different: The performance in the Corn, Wheat and the S&P 500 futures alone would clearly outperform all other benchmark investments.

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[18] Consider, for instance, direct equity investments for the two equity indices and warrants for the DJ AIG Commodity Index.

Analyses in chapters 3 and 4 have delivered some findings that could be helpful to any practitioner who considers using disclosed trading positions for market timing purposes: The most important result is that the systematic and well considered selection of futures contracts one wants to trade in is indispensable. The benchmark results have shown that superior returns can not be expected from the sentiment-based trading strategy when it is applied to a portfolio of randomly selected futures markets. Before deciding to implement this strategy in a futures market is should be empirically tested if there has been a historical relation between trading positions and returns in subsequent periods. One possible approach to investigate this relationship would be a regression framework like the one presented in section 3.2. In addition, it should be investigated whether the found relations have remained stable over time. Regression results for several sub-samples revealed that market conditions seem to have changed in many cases so that trading positions could not be interpreted in the same way as in the past. Reasons for such changes in market structures are manifold: New traders entering the market, existing traders leaving the market, changes in risk premia and hedging demand, changing forecasting skills, to name a few. It is recommended to apply the sentiment-based trading strategy only to markets that did not exhibit any structural breaks in the past. Evidence has shown that the S&P 500 contract might be a good starting point. But even if sub-sample tests have shown consistent results, there is still the risk that this might change in the near future. If market patterns remain sustained, however, then chances of high returns exist. Results in Table 13 prove that in such markets environments, annual returns greater than 50% and hit ratios beyond 70% are within the bounds of economic possibility. Another finding is that small traders seem to be positioned wrong in majority of cases. This discovery could also be used for trading purposes, for example by implementing a contrary strategy. Furthermore, results have shown that extreme sentiment levels provide the most distinctive trading results – be it positive or negative. Given that a trader has found a futures market with a consistent history of market patterns, it is recommended to set the threshold value to 1. The sensitivity analysis has proven that this threshold level generated the best market timing signals – provided that one is positioned on the right side of the market, of course. In the examples for the trading strategy so far, only entry signals have been dependent on the values of the sentiment index. So far, the positions have been held over the predetermined holding period, regardless of the further developments in investors' sentiment. It is very likely, however, that the trading performance would be enhanced the sentiment-based indices would also be used to time market exits.

5 Conclusion

This thesis investigated the relation between trading positions and returns in futures markets. In total, 10 futures contracts from different categories have been analyzed with a consistent methodology. Results show that hedgers reduce their net positions in periods of rising futures prices, while speculators increase their holdings in periods of appreciating prices. This observation applies to all markets investigated. Relatively high coefficients of determination indicate rather strong relations between trading positions and futures prices. Apart from these findings, there seem to be few similarities across different futures contracts, however. The questions of risk premia and forecasting abilities are good examples: There, obtained results differ significantly across the markets.

The papers by Wang (2001, 2003) drew a delightful picture. He found the same patterns in all futures he analyzed and suggested that levels of investor sentiment can be used as market timing indicators. This thesis has shown that these findings probably are “too good to be true”: While forecasting futures returns by means of disclosed trading positions may be possible, there are two factors that complicate such endeavors: Firstly, investor sentiment has to be interpreted differently for each market. Secondly, and even worse, the way these signals need to interpreted can change over time. Therefore, Wang’s (2001) conclusion that “large speculator sentiment is a price continuation indicator, whereas large hedger sentiment is a contrary indicator” should be taken with caution.

In this sense, one of the scientific contributions of this thesis is that a varied portfolio of futures contracts has been analyzed with a consistent methodology. This way, differences between futures contracts could be identified. Furthermore, initial empirical evidence on a wide range of contracts has been presented. The yet scarce literature on the use of trading positions for forecasting purposes has been extended. Finally, the feasibility of a sentiment-based futures trading strategy has been investigated for the first time.

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Appendix A: Sub-sample regression results

Appendix A contains the regression results of regression equation (6) from section 3.2 for the three sub-sample periods.

Data sources for Tables 14, 15 and 16: CFTC COT reports (trading positions), Datastream (contract prices). Sample periods as indicated below.

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

Table 14: Sub-sample 1 (01/01/1995 – 12/31/1998)

PANEL A: COMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.1064	(-5.49)	-0.0517	(-2.16)	0.0220	(0.81)	0.0643	(4.06)	-0.0077	(-0.47)	0.0013	(0.12)	0.0468	(5.02)	-0.0008	(-0.37)	0.0218	(2.43)	0.0501	(1.80)
	R^2	0.12	***	0.02	**	0.00		0.07	***	0.00		0.00		0.12	***	0.00		0.02	**	0.03	*
60 days	β	-0.1739	(-5.76)	-0.0463	(-1.36)	0.0043	(0.10)	0.1128	(5.58)	0.0234	(0.96)	0.0160	(1.15)	0.0831	(6.30)	0.0015	(0.45)	0.0200	(1.65)	0.0935	(2.63)
	R^2	0.13	***	0.01		0.00		0.13	***	0.00		0.01		0.18	***	0.00		0.01	*	0.06	***
90 days	β	-0.2177	(-5.67)	-0.0547	(-1.18)	-0.0195	(-0.45)	0.1498	(7.93)	0.0731	(2.39)	0.0180	(1.07)	0.1149	(6.81)	0.0078	(2.15)	0.0166	(1.14)	0.1522	(3.83)
	R^2	0.12	***	0.01		0.00		0.20	***	0.03	**	0.01		0.22	***	0.03	**	0.01		0.12	***
130 days	β	-0.2400	(-5.02)	-0.0406	(-0.71)	-0.0820	(-1.62)	0.1601	(6.59)	0.1326	(4.10)	0.0444	(2.42)	0.1312	(6.99)	0.0119	(3.10)	-0.0156	(-1.02)	0.2301	(6.28)
	R^2	0.10	***	0.00		0.01		0.21	***	0.09	***	0.03	**	0.21	***	0.05	***	0.00		0.21	***
260 days	β	-0.1948	(-2.36)	-0.1398	(0.67)	-0.3822	(-4.69)	0.0958	(4.97)	0.0784	(1.42)	-0.0110	(-0.50)	0.0877	(3.11)	0.0270	(6.52)	-0.0408	(-1.34)	0.2410	(8.09)
	R^2	0.04	**	0.00		0.08	***	0.08	***	0.02		0.00		0.06	***	0.17	***	0.01		0.23	***

PANEL B: NONCOMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0867	(5.11)	0.0754	(3.54)	-0.0250	(-0.93)	-0.0361	(-2.32)	0.0135	(0.85)	-0.0046	(-0.43)	-0.0453	(-5.32)	0.0046	(1.77)	-0.0181	(-2.15)	-0.0354	(-1.31)
	R^2	0.09	***	0.06	***	0.00		0.03	**	0.00		0.00		0.13	***	0.02	*	0.02	**	0.02	
60 days	β	0.1470	(5.37)	0.1287	(4.63)	-0.0209	(-0.49)	-0.0702	(-3.69)	-0.0127	(-0.58)	-0.0259	(-1.86)	-0.0771	(-6.13)	0.0034	(1.01)	-0.0154	(-1.35)	-0.0702	(-1.91)
	R^2	0.10	***	0.10	***	0.00		0.07	***	0.00		0.02	*	0.18	***	0.01		0.01		0.04	*
90 days	β	0.2023	(5.70)	0.1706	(4.94)	-0.0015	(-0.04)	-0.1138	(-6.92)	-0.0484	(-1.76)	-0.0305	(-1.84)	-0.1097	(-7.01)	-0.0023	(-0.57)	-0.0117	(-0.82)	-0.1267	(-2.99)
	R^2	0.11	***	0.12	***	0.00		0.15	***	0.02	*	0.02	*	0.22	***	0.00		0.00		0.09	***
130 days	β	0.2579	(6.10)	0.1862	(4.34)	0.0622	(1.29)	-0.1137	(-5.10)	-0.0936	(-3.20)	-0.0635	(-3.42)	-0.1337	(-7.73)	-0.0082	(-1.89)	0.0175	(1.21)	-0.2087	(-5.21)
	R^2	0.13	***	0.10	***	0.01		0.13	***	0.06	***	0.05	***	0.25	***	0.02	*	0.01		0.18	***
260 days	β	0.2991	(3.70)	0.1180	(1.86)	0.3582	(4.48)	-0.0102	(-0.63)	-0.0136	(-0.26)	-0.0106	(-0.44)	-0.1169	(-4.51)	-0.0204	(-4.03)	0.0496	(1.65)	-0.2294	(-7.16)
	R^2	0.11	***	0.02		0.07	***	0.00		0.00		0.00		0.11	***	0.08	***	0.02	*	0.22	***

PANEL C: NONREPORTABLES

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0126	(0.52)	-0.0738	(-3.38)	-0.0042	(-0.13)	-0.0386	(-3.39)	-0.0065	(-0.41)	-0.0008	(-0.08)	-0.0186	(-2.30)	-0.0049	(-2.22)	-0.0387	(-3.91)	-0.1076	(-4.05)
	R^2	0.00		0.06	***	0.00		0.04	***	0.00		0.00		0.03	**	0.03	**	0.06	***	0.07	***
60 days	β	0.0089	(0.24)	-0.2085	(-7.41)	0.0546	(1.05)	-0.0656	(-5.27)	-0.0356	(-1.37)	-0.0033	(-0.24)	-0.0356	(-3.42)	-0.0101	(-3.24)	-0.0472	(-3.56)	-0.1152	(-2.82)
	R^2	0.00		0.26	***	0.01		0.06	***	0.01		0.00		0.05	***	0.07	***	0.05	***	0.05	***
90 days	β	-0.0479	(-1.10)	-0.2969	(-10.30)	0.1063	(1.94)	-0.0773	(-5.94)	-0.0871	(-2.76)	0.0015	(0.08)	-0.0516	(-4.29)	-0.0159	(-4.16)	-0.0462	(-3.01)	-0.1260	(-2.63)
	R^2	0.00		0.37	***	0.02		0.07	***	0.04	***	0.00		0.07	***	0.11	***	0.04	***	0.04	***
130 days	β	-0.1728	(-3.53)	-0.3740	(-10.62)	0.2144	(3.63)	-0.0915	(-5.68)	-0.1455	(-4.51)	-0.0144	(-0.78)	-0.0573	(-3.97)	-0.0186	(-5.78)	-0.0156	(-0.93)	-0.1022	(-1.80)
	R^2	0.04	***	0.40	***	0.06	***	0.09	***	0.10	***	0.00		0.06	***	0.12	***	0.00		0.02	*
260 days	β	-0.3382	(-4.84)	-0.4532	(-7.49)	0.6611	(7.61)	-0.0789	(-4.94)	-0.1165	(-2.47)	0.0555	(2.49)	-0.0259	(-1.24)	-0.0339	(-8.72)	-0.0487	(-1.75)	-0.0283	(-0.53)
	R^2	0.10	***	0.36	***	0.19	***	0.07	***	0.04	**	0.03	**	0.01		0.26	***	0.01	*	0.00	

Table 15: Sub-sample 2 (01/01/1999 – 12/31/2002)

PANEL A: COMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0623	(2.47)	0.0481	(2.06)	-0.0522	(-1.82)	0.1055	(5.75)	-0.0044	(-0.28)	-0.0078	(-0.65)	0.0094	(0.68)	0.0014	(0.57)	-0.0062	(-0.45)	0.0328	(2.42)
	R^2	0.04	**	0.03	**	0.01	*	0.12	***	0.00		0.00		0.00		0.00		0.00		0.04	**
60 days	β	0.1821	(5.60)	0.1216	(3.57)	-0.1347	(-3.32)	0.1588	(7.23)	0.0085	(0.39)	0.0096	(0.58)	-0.0051	(-0.28)	0.0034	(0.92)	-0.0169	(-0.81)	0.0224	(1.52)
	R^2	0.18	***	0.10	***	0.06	***	0.18	***	0.00		0.00		0.00		0.01		0.01		0.02	
90 days	β	0.2659	(7.64)	0.2014	(5.10)	-0.2179	(-3.99)	0.1888	(8.60)	0.0448	(1.50)	0.0425	(2.25)	-0.0060	(-0.32)	0.0060	(1.32)	-0.0161	(-0.68)	0.0175	(1.06)
	R^2	0.31	***	0.18	***	0.10	***	0.19	***	0.02		0.03	**	0.00		0.01		0.00		0.01	
130 days	β	0.2935	(9.19)	0.2938	(6.98)	-0.2777	(-4.50)	0.2674	(11.51)	0.0600	(2.20)	-0.0110	(-0.48)	-0.0141	(-0.67)	0.0077	(1.55)	-0.0057	(-0.26)	0.0212	(1.22)
	R^2	0.37	***	0.32	***	0.12	***	0.27	***	0.03	**	0.00		0.00		0.02		0.00		0.01	
260 days	β	0.2303	(7.70)	0.1071	(3.32)	-0.2248	(-3.01)	0.4262	(10.70)	-0.0187	(-0.61)	-0.0918	(-2.42)	0.0148	(0.59)	0.0212	(2.54)	-0.0790	(-3.73)	0.0767	(3.39)
	R^2	0.24	***	0.06	***	0.04	***	0.30	***	0.00		0.04	**	0.00		0.06	**	0.05	***	0.05	***

PANEL B: NONCOMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.0571	(-2.26)	-0.0334	(-1.50)	0.0527	(1.82)	-0.0272	(-1.43)	0.0059	(0.33)	0.0075	(0.56)	0.0081	(0.69)	-0.0010	(-0.37)	0.0039	(0.27)	-0.0351	(-2.48)
	R^2	0.04	**	0.02		0.01	*	0.02	***	0.00		0.00		0.00		0.00		0.00		0.04	**
60 days	β	-0.1859	(-5.46)	-0.0912	(-2.76)	0.1386	(3.41)	-0.0574	(-2.96)	-0.0110	(-0.43)	-0.0145	(-0.78)	0.0359	(2.24)	-0.0013	(-0.35)	0.0123	(0.58)	-0.0226	(-1.43)
	R^2	0.19	***	0.06	***	0.06	***	0.05	***	0.00		0.00		0.03	**	0.00		0.00		0.01	
90 days	β	-0.2747	(-7.81)	-0.1693	(-4.55)	0.2221	(4.13)	-0.0721	(-3.21)	-0.0456	(-1.32)	-0.0569	(-2.61)	0.0443	(2.75)	-0.0016	(-0.36)	0.0074	(0.31)	-0.0187	(-1.07)
	R^2	0.33	***	0.14	***	0.10	***	0.05	***	0.02		0.03	***	0.03	***	0.00		0.00		0.01	
130 days	β	-0.3150	(-10.92)	-0.2561	(-6.58)	0.2767	(4.53)	-0.1367	(-6.19)	-0.0591	(-1.87)	-0.0107	(-0.40)	0.0596	(3.13)	-0.0048	(-0.94)	-0.0048	(-0.22)	-0.0165	(-0.90)
	R^2	0.42	***	0.27	***	0.11	***	0.14	***	0.03	*	0.00		0.04	***	0.01		0.00		0.00	
260 days	β	-0.2530	(-8.82)	-0.0850	(-2.74)	0.2480	(3.23)	-0.3160	(-11.42)	0.0451	(1.32)	0.0758	(1.58)	-0.0030	(-0.11)	-0.0188	(-2.11)	0.0675	(3.09)	-0.0791	(-3.26)
	R^2	0.29	***	0.04	***	0.05	***	0.32	***	0.01		0.02		0.00		0.04	**	0.04	***	0.05	***

PANEL C: NONREPORTABLES

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.0326	(-1.37)	-0.0699	(-2.34)	0.0791	(2.29)	-0.1340	(-6.38)	0.0067	(0.61)	0.0016	(0.13)	-0.0425	(-3.09)	-0.0027	(-0.86)	0.0208	(1.83)	0.0010	(0.07)
	R^2	0.01		0.04	**	0.03	**	0.15	***	0.00		0.00		0.06	***	0.01		0.01	*	0.00	
60 days	β	-0.0407	(-1.18)	-0.0772	(-1.76)	0.1963	(4.29)	-0.1808	(-6.94)	0.0068	(0.48)	-0.0201	(-1.20)	-0.0655	(-4.50)	-0.0079	(-1.96)	0.0385	(2.26)	0.0070	(0.41)
	R^2	0.01		0.02	*	0.09	***	0.18	***	0.00		0.01		0.08	***	0.02	**	0.03	**	0.00	
90 days	β	-0.0055	(-0.15)	-0.0096	(-0.18)	0.3166	(5.73)	-0.2339	(-7.11)	-0.0257	(-1.44)	-0.0572	(-2.90)	-0.0868	(-4.71)	-0.0147	(-2.89)	0.0567	(3.03)	0.0045	(0.24)
	R^2	0.00		0.00		0.16	***	0.22	***	0.01		0.05	***	0.10	***	0.05	***	0.06	***	0.00	
130 days	β	0.0479	(1.30)	0.0008	(0.02)	0.4380	(6.63)	-0.2712	(-7.78)	-0.0412	(-2.20)	-0.0089	(-0.40)	-0.1085	(-5.37)	-0.0143	(-2.61)	0.0605	(3.19)	-0.0165	(-1.10)
	R^2	0.01		0.00		0.22	***	0.21	***	0.02	**	0.00		0.12	***	0.03	***	0.05	***	0.00	
260 days	β	0.0117	(0.33)	-0.0856	(-2.18)	0.3707	(4.55)	-0.4113	(-7.51)	-0.0053	(-0.23)	0.0599	(1.57)	-0.0494	(-1.93)	-0.0332	(-4.08)	0.1394	(7.83)	-0.0017	(-0.06)
	R^2	0.00		0.02	**	0.08	***	0.21	***	0.00		0.02		0.02	*	0.09	***	0.16	***	0.00	

Table 16: Sub-sample 3 (01/01/2003 – 12/30/2006)

PANEL A: COMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.0108	(-0.49)	0.0706	(3.44)	0.0628	(2.26)	0.0371	(3.52)	-0.0047	(-0.73)	0.0185	(2.21)	0.0201	(2.25)	-0.0014	(-0.99)	0.0399	(2.56)	0.0462	(1.30)
	R^2	0.00		0.04	***	0.02	**	0.06	***	0.00		0.03	**	0.03	**	0.01		0.02	**	0.01	
60 days	β	0.0016	(0.04)	0.0603	(2.09)	0.0971	(2.78)	0.0436	(2.87)	-0.0100	(-1.23)	0.0295	(2.74)	0.0422	(3.96)	-0.0014	(-0.73)	0.0257	(1.29)	0.0513	(1.23)
	R^2	0.00		0.02	**	0.03	***	0.05	***	0.01		0.04	***	0.07	***	0.00		0.01		0.01	
90 days	β	0.0515	(0.94)	0.1120	(3.09)	0.0812	(2.10)	0.0290	(1.59)	-0.0215	(-2.04)	0.0076	(0.62)	0.0310	(2.54)	0.0003	(0.11)	0.0159	(0.57)	0.0605	(1.24)
	R^2	0.01		0.06	***	0.02	**	0.02		0.02	**	0.00		0.03	**	0.00		0.00		0.01	
130 days	β	0.1811	(2.66)	0.1974	(4.84)	-0.0038	(-0.08)	0.0055	(0.25)	-0.0162	(-1.26)	0.0200	(1.40)	0.0207	(1.64)	0.0019	(0.89)	0.0756	(2.17)	0.1184	(2.24)
	R^2	0.07	***	0.13	***	0.00		0.00		0.01		0.01		0.02		0.00		0.03	**	0.03	**
260 days	β	0.4485	(9.13)	0.4869	(0.49)	-0.1470	(-2.47)	0.0277	(0.65)	-0.0556	(-3.94)	0.0131	(0.63)	0.0299	(1.99)	-0.0014	(-0.51)	0.1964	(4.73)	0.4511	(8.01)
	R^2	0.31	***	0.50		0.05	**	0.01		0.07	***	0.00		0.02	**	0.00		0.16	***	0.31	***

PANEL B: NONCOMMERCIALS

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	0.0213	(1.07)	-0.0478	(-2.72)	-0.0539	(-1.89)	-0.0029	(-0.39)	0.0060	(0.95)	-0.0175	(-2.10)	-0.0285	(-2.95)	0.0008	(0.68)	-0.0345	(-2.23)	-0.0356	(-1.02)
	R^2	0.00		0.03	***	0.02	*	0.00		0.00		0.02	**	0.05	***	0.00		0.02	**	0.01	
60 days	β	0.0290	(0.87)	-0.0275	(-1.04)	-0.0628	(-1.98)	-0.0142	(-1.19)	0.0129	(1.63)	-0.0256	(-2.29)	-0.0536	(-4.55)	0.0021	(1.14)	-0.0143	(-0.73)	-0.0481	(-1.18)
	R^2	0.00		0.01		0.02	**	0.01		0.01		0.03	**	0.11	***	0.01		0.00		0.01	
90 days	β	-0.0130	(-0.27)	-0.0699	(-2.17)	-0.0459	(-1.33)	-0.0248	(-1.78)	0.0253	(2.42)	0.0000	(0.00)	-0.0530	(-4.39)	0.0008	(0.37)	0.0051	(0.19)	-0.0556	(-1.19)
	R^2	0.00		0.03	**	0.01		0.02	*	0.03	**	0.00		0.10	***	0.00		0.00		0.01	
130 days	β	-0.1004	(-1.56)	-0.1513	(-4.10)	0.0436	(1.04)	-0.0325	(-1.88)	0.0215	(1.73)	-0.0093	(-0.63)	-0.0336	(-2.58)	-0.0023	(-1.10)	-0.0365	(-1.09)	-0.1139	(-2.31)
	R^2	0.02		0.10	***	0.01		0.03	*	0.02	*	0.00		0.04	***	0.01		0.01		0.03	**
260 days	β	-0.4719	(-9.51)	-0.4531	(-12.66)	0.2175	(4.19)	-0.0255	(-1.66)	0.0743	(5.55)	-0.0026	(-0.12)	-0.0432	(-2.42)	0.0063	(2.25)	-0.1338	(-3.08)	-0.4029	(-7.63)
	R^2	0.35	***	0.52	***	0.12	***	0.01	*	0.13	***	0.00		0.04	**	0.03	**	0.08	***	0.30	***

PANEL C: NONREPORTABLES

HP	Variable	Corn		Wheat		Oil		SP500		JPY		CHF		Bond		Note		Gold		Silver	
30 days	β	-0.0493	(-1.94)	0.0177	(0.50)	-0.0382	(-0.86)	-0.0443	(-3.34)	-0.0044	(-0.50)	-0.0198	(-2.11)	-0.0016	(-0.18)	0.0019	(1.25)	-0.0811	(-4.78)	-0.0530	(-1.73)
	R^2	0.01	*	0.00		0.01		0.06	***	0.00		0.03	**	0.00		0.01		0.09	***	0.02	*
60 days	β	-0.0661	(-1.71)	-0.0213	(-0.53)	-0.1292	(-2.52)	-0.0387	(-2.16)	-0.0104	(-0.99)	-0.0357	(-3.06)	-0.0249	(-1.73)	0.0016	(0.82)	-0.1267	(-5.85)	-0.0701	(-1.94)
	R^2	0.01	*	0.00		0.04	**	0.03	**	0.00		0.05	***	0.01	*	0.00		0.18	***	0.02	*
90 days	β	-0.0391	(-0.85)	-0.0480	(-1.09)	-0.1100	(-2.16)	-0.0071	(-0.31)	-0.0071	(-0.48)	-0.0162	(-1.25)	-0.0275	(-1.40)	0.0017	(0.65)	-0.1704	(-7.33)	-0.1004	(-2.38)
	R^2	0.00		0.01		0.03	**	0.00		0.00		0.01		0.01		0.00		0.22	***	0.04	**
130 days	β	-0.0695	(-1.16)	-0.0697	(-1.46)	-0.1001	(-1.64)	0.0298	(0.99)	-0.0295	(-1.65)	-0.0297	(-2.01)	-0.0588	(-2.88)	0.0003	(0.10)	-0.2652	(-8.96)	-0.1413	(-2.65)
	R^2	0.01		0.01		0.02		0.01		0.02	*	0.02	**	0.05	***	0.00		0.37	***	0.05	***
260 days	β	0.5071	(6.60)	0.0124	(0.19)	-0.0616	(-0.84)	-0.0342	(-1.03)	-0.0299	(-1.21)	-0.0113	(-0.53)	-0.0439	(-1.59)	-0.0046	(-1.16)	-0.3601	(-10.84)	-0.4222	(-8.84)
	R^2	0.21	***	0.00		0.01		0.01		0.01		0.00		0.02		0.01		0.56	***	0.34	***

Appendix B: Sensitivity analysis data

Appendix B contains the underlying data of Figure 5 (see section 4.3)

Table 17: Sensitivity analysis data

Panel A: Commercials

	Sentiment index threshold															
Hold. Per.	**1.00**	**0.98**	**0.96**	**0.94**	**0.92**	**0.90**	**0.88**	**0.86**	**0.84**	**0.82**	**0.80**	**0.78**	**0.76**	**0.74**	**0.72**	**0.70**
30	9.1%	9.0%	4.5%	1.4%	1.7%	0.5%	-1.2%	-0.6%	-2.2%	-1.9%	-2.7%	-1.2%	0.6%	-0.9%	-0.6%	1.8%
34	6.7%	7.4%	4.9%	1.6%	1.0%	-0.5%	-2.0%	-1.3%	-1.0%	-1.4%	-2.6%	-1.1%	0.6%	-1.6%	-2.0%	0.6%
38	5.8%	8.5%	5.0%	2.0%	1.8%	-0.4%	-2.4%	-1.6%	-2.1%	-3.1%	-4.1%	-2.5%	1.4%	-0.9%	-1.5%	0.0%
42	5.1%	7.2%	4.6%	2.1%	1.9%	0.6%	-1.6%	-0.5%	-0.8%	-2.2%	-2.6%	-1.4%	1.4%	-0.6%	-1.3%	0.6%
46	4.6%	7.8%	4.5%	2.6%	2.2%	1.4%	-0.7%	-0.2%	-0.1%	-1.4%	-2.5%	-0.4%	1.3%	-0.1%	-0.3%	1.1%
50	3.8%	6.1%	4.3%	2.1%	2.5%	1.6%	-0.8%	-1.3%	-1.0%	-1.4%	-2.4%	-1.0%	1.1%	-0.1%	0.0%	1.3%
54	3.8%	5.7%	3.4%	2.0%	2.5%	1.0%	0.0%	-0.2%	0.3%	-0.7%	-2.3%	-0.7%	1.9%	0.7%	0.3%	1.4%
58	3.9%	5.7%	3.5%	1.2%	1.3%	0.4%	-0.7%	-1.0%	-0.3%	-0.8%	-1.8%	-0.2%	1.4%	-0.2%	-0.1%	1.1%
62	3.9%	4.2%	2.7%	0.4%	1.0%	0.0%	-1.0%	-0.8%	-0.5%	-1.1%	-2.1%	-0.7%	1.3%	-0.2%	-0.3%	0.9%
66	4.8%	4.8%	2.9%	1.0%	1.2%	-0.4%	-1.7%	-1.7%	-0.7%	-1.5%	-2.6%	-0.9%	0.3%	-0.7%	-0.8%	0.5%
70	3.5%	4.6%	2.5%	1.8%	1.3%	-0.9%	-2.0%	-1.4%	-1.0%	-1.8%	-2.2%	-0.5%	0.5%	-0.6%	-0.7%	0.3%
74	3.9%	4.9%	3.1%	1.9%	1.6%	-0.5%	-1.8%	-1.8%	-1.5%	-2.0%	-2.9%	-1.3%	-0.1%	-1.2%	-1.3%	-0.1%
78	3.4%	4.8%	3.0%	1.2%	1.2%	-1.1%	-2.7%	-2.9%	-1.7%	-2.3%	-3.3%	-1.6%	-0.2%	-1.1%	-1.3%	-0.4%
82	3.3%	4.7%	3.3%	1.2%	1.4%	-0.7%	-2.6%	-2.9%	-2.4%	-2.9%	-3.7%	-2.3%	-0.7%	-1.0%	-1.2%	-0.6%
86	3.5%	4.3%	3.0%	1.2%	1.1%	-1.0%	-2.2%	-2.4%	-2.0%	-2.2%	-3.3%	-1.9%	-0.6%	-1.0%	-1.0%	-0.3%
90	3.3%	3.8%	2.5%	0.9%	0.7%	-0.9%	-2.3%	-2.3%	-2.4%	-2.6%	-3.6%	-2.4%	-0.9%	-1.4%	-1.1%	-0.2%
94	4.2%	4.3%	2.6%	1.0%	0.8%	-0.6%	-2.3%	-2.3%	-2.4%	-2.3%	-3.0%	-1.9%	-0.6%	-1.2%	-1.3%	-0.7%
98	4.3%	4.6%	3.2%	1.2%	1.0%	-0.5%	-2.5%	-2.7%	-2.9%	-2.7%	-3.3%	-2.4%	-1.2%	-1.6%	-1.6%	-0.7%
102	5.4%	5.1%	3.3%	0.7%	0.4%	-0.5%	-2.2%	-2.5%	-2.1%	-2.5%	-3.0%	-2.1%	-1.0%	-1.3%	-1.3%	-0.4%
106	5.8%	5.6%	3.3%	1.1%	1.1%	0.0%	-1.9%	-2.5%	-1.6%	-1.7%	-2.4%	-1.9%	-0.8%	-1.2%	-1.2%	0.0%
110	6.1%	5.9%	3.9%	1.7%	1.1%	0.0%	-1.6%	-1.8%	-1.1%	-1.4%	-2.1%	-1.4%	-0.4%	-0.7%	-0.8%	0.5%
114	5.1%	5.2%	3.7%	1.6%	1.3%	0.1%	-2.0%	-2.0%	-1.0%	-1.4%	-2.1%	-1.5%	-0.4%	-0.4%	-0.8%	0.3%
118	5.1%	5.1%	3.6%	1.5%	1.1%	0.1%	-1.4%	-1.6%	-0.8%	-1.6%	-2.1%	-1.2%	-0.5%	-0.6%	-0.9%	0.3%
122	4.4%	4.9%	3.1%	1.3%	0.9%	-0.3%	-1.5%	-1.6%	-0.8%	-1.4%	-2.0%	-1.5%	-0.9%	-1.1%	-1.3%	-0.1%
126	4.9%	5.1%	3.3%	1.9%	1.3%	-0.1%	-1.6%	-1.4%	-0.6%	-1.3%	-1.7%	-1.0%	-0.7%	-1.1%	-1.5%	-0.1%
130	5.6%	5.3%	3.2%	1.5%	1.5%	-0.1%	-1.8%	-1.5%	-0.5%	-1.3%	-1.6%	-1.1%	-0.5%	-0.8%	-1.1%	-0.1%
134	5.5%	5.1%	3.2%	2.0%	1.5%	0.3%	-1.0%	-1.0%	-0.3%	-1.0%	-1.5%	-1.0%	-0.4%	-0.8%	-1.1%	0.0%
138	5.3%	5.0%	3.0%	1.6%	0.7%	-0.4%	-1.2%	-0.8%	0.1%	-0.7%	-1.3%	-1.0%	-0.7%	-1.0%	-1.2%	-0.1%
142	5.4%	5.2%	3.1%	1.6%	0.9%	-0.6%	-1.3%	-0.7%	0.2%	-0.5%	-1.0%	-0.8%	-0.7%	-1.4%	-1.8%	-0.5%
146	5.1%	4.9%	2.8%	1.6%	1.0%	-0.3%	-1.2%	-0.8%	0.1%	-0.9%	-1.0%	-0.9%	-0.4%	-1.1%	-1.6%	-0.3%
150	4.5%	4.5%	2.6%	1.2%	0.3%	-0.6%	-1.4%	-1.2%	-0.1%	-0.9%	-1.2%	-1.0%	-0.3%	-0.7%	-1.4%	-0.3%
154	4.2%	4.6%	2.6%	1.2%	0.2%	-0.5%	-1.5%	-1.1%	0.2%	-0.8%	-1.3%	-1.2%	-0.5%	-1.0%	-1.4%	-0.4%
158	3.9%	4.0%	2.3%	1.0%	0.4%	-0.2%	-1.2%	-0.9%	0.1%	-0.9%	-1.3%	-1.2%	-0.7%	-0.8%	-1.1%	-0.1%
162	4.4%	4.1%	2.2%	0.9%	0.4%	-0.5%	-1.4%	-1.1%	-0.2%	-1.2%	-1.6%	-1.2%	-0.6%	-0.9%	-1.4%	-0.5%
166	4.0%	3.7%	2.0%	0.7%	0.2%	-0.4%	-1.5%	-1.4%	-0.4%	-1.4%	-1.7%	-1.3%	-0.7%	-1.0%	-1.3%	-0.3%
170	3.6%	3.2%	1.7%	0.7%	0.1%	-0.4%	-1.5%	-1.2%	-0.3%	-1.4%	-1.6%	-1.0%	-0.3%	-0.6%	-1.0%	0.0%
174	3.6%	3.1%	1.7%	0.4%	0.2%	-0.3%	-1.5%	-1.3%	-0.4%	-1.5%	-1.8%	-1.3%	-0.8%	-1.1%	-1.2%	-0.1%
178	3.7%	2.8%	1.5%	0.3%	0.1%	-0.4%	-1.4%	-1.1%	-0.1%	-1.3%	-1.6%	-1.1%	-0.6%	-1.1%	-1.0%	-0.1%
182	4.1%	3.0%	1.7%	0.1%	-0.1%	-0.4%	-1.4%	-0.8%	-0.1%	-1.2%	-1.6%	-1.0%	-0.7%	-1.2%	-1.2%	-0.2%
186	4.2%	2.9%	1.3%	0.0%	0.0%	-0.4%	-1.3%	-1.0%	-0.1%	-1.2%	-1.6%	-1.1%	-0.8%	-1.3%	-1.3%	-0.3%
190	4.0%	2.9%	1.2%	0.0%	0.1%	-0.3%	-1.1%	-1.0%	-0.4%	-1.5%	-1.8%	-1.1%	-0.6%	-1.1%	-1.0%	-0.3%
194	4.0%	3.0%	1.5%	0.1%	0.0%	-0.2%	-1.1%	-1.1%	-0.7%	-1.8%	-1.9%	-1.4%	-1.0%	-1.4%	-1.3%	-0.3%
198	3.8%	2.6%	1.2%	0.2%	-0.1%	-0.1%	-1.0%	-1.1%	-0.7%	-1.8%	-2.1%	-1.5%	-1.1%	-1.6%	-1.4%	-0.4%
202	3.1%	2.4%	0.9%	0.0%	-0.3%	-0.4%	-1.1%	-0.9%	-0.7%	-1.8%	-2.2%	-1.6%	-1.2%	-1.7%	-1.5%	-0.5%
206	3.1%	2.4%	1.0%	0.2%	0.0%	-0.3%	-1.3%	-0.9%	-0.7%	-1.7%	-2.1%	-1.3%	-1.1%	-1.8%	-1.5%	-0.7%
210	2.7%	2.4%	1.2%	0.4%	0.0%	-0.3%	-1.3%	-1.0%	-1.0%	-2.0%	-2.3%	-1.5%	-0.9%	-1.7%	-1.6%	-0.7%
214	2.7%	2.4%	0.7%	-0.1%	-0.5%	-0.5%	-1.1%	-1.0%	-0.6%	-1.6%	-1.9%	-1.1%	-0.6%	-1.3%	-1.2%	-0.4%
218	2.4%	2.1%	0.4%	-0.1%	-0.3%	-0.5%	-1.2%	-1.1%	-0.6%	-1.7%	-1.8%	-1.3%	-0.8%	-1.4%	-1.2%	-0.4%
222	2.2%	1.9%	0.4%	-0.3%	-0.6%	-0.6%	-1.3%	-1.3%	-0.9%	-1.9%	-2.1%	-1.7%	-0.9%	-1.6%	-1.5%	-0.5%
226	2.4%	2.3%	0.7%	-0.3%	-0.5%	-0.8%	-1.5%	-1.3%	-0.9%	-1.9%	-1.9%	-1.4%	-0.8%	-1.4%	-1.3%	-0.5%
230	2.0%	1.9%	0.3%	-0.5%	-0.9%	-1.3%	-2.0%	-1.6%	-1.1%	-2.1%	-2.2%	-1.6%	-0.9%	-1.6%	-1.5%	-0.7%
234	1.7%	1.6%	0.2%	-0.6%	-0.9%	-1.2%	-1.9%	-1.7%	-1.2%	-2.2%	-2.4%	-2.0%	-1.2%	-1.8%	-1.7%	-0.8%
238	1.6%	1.4%	0.0%	-0.7%	-1.0%	-1.3%	-2.0%	-1.7%	-1.2%	-2.3%	-2.6%	-2.0%	-1.2%	-1.7%	-1.5%	-0.7%
242	1.4%	1.4%	0.0%	-0.5%	-0.7%	-0.9%	-1.8%	-1.6%	-1.3%	-2.3%	-2.5%	-1.9%	-1.3%	-1.8%	-1.6%	-0.7%
246	1.2%	1.3%	0.1%	-0.8%	-0.9%	-1.2%	-1.9%	-1.6%	-1.1%	-2.1%	-2.4%	-1.8%	-1.1%	-1.7%	-1.5%	-0.7%
250	1.1%	0.9%	-0.4%	-1.2%	-1.2%	-1.3%	-1.9%	-1.4%	-0.9%	-1.9%	-2.1%	-1.7%	-1.0%	-1.8%	-1.6%	-0.9%
254	0.8%	0.7%	-0.5%	-1.2%	-1.2%	-1.4%	-1.9%	-1.6%	-1.2%	-2.0%	-2.2%	-1.7%	-1.1%	-1.7%	-1.7%	-0.7%
258	1.2%	0.7%	-0.5%	-1.3%	-1.6%	-1.7%	-2.2%	-1.8%	-1.3%	-2.1%	-2.2%	-1.7%	-0.9%	-1.4%	-1.5%	-0.5%

Panel B: Noncommercials

	Sentiment index threshold															
Hold. Per.	**1.00**	**0.98**	**0.96**	**0.94**	**0.92**	**0.90**	**0.88**	**0.86**	**0.84**	**0.82**	**0.80**	**0.78**	**0.76**	**0.74**	**0.72**	**0.70**
30	-2.6%	-1.7%	-0.9%	1.4%	2.4%	4.5%	1.2%	0.3%	-0.8%	-1.0%	1.2%	1.4%	0.2%	-0.5%	-0.7%	-1.5%
34	-0.8%	-0.6%	-0.2%	1.0%	1.2%	3.9%	1.4%	1.1%	0.0%	-0.4%	0.2%	1.1%	0.5%	-0.4%	0.1%	-0.7%
38	1.0%	1.4%	1.1%	2.5%	2.0%	3.6%	2.6%	1.9%	0.4%	0.1%	1.7%	1.3%	0.7%	0.9%	1.5%	0.3%
42	1.6%	2.1%	2.9%	3.3%	2.3%	3.3%	2.3%	2.1%	0.6%	0.3%	2.5%	2.7%	1.9%	0.3%	1.1%	-0.4%
46	1.7%	1.5%	1.6%	2.1%	1.6%	2.1%	1.5%	1.7%	0.6%	0.3%	1.4%	1.0%	-0.1%	-0.3%	0.0%	-1.1%
50	1.6%	1.8%	2.2%	2.6%	1.4%	1.7%	0.5%	2.3%	0.7%	0.8%	1.9%	1.8%	0.7%	-0.1%	0.2%	-0.7%
54	3.3%	3.1%	2.6%	2.2%	1.2%	1.3%	0.0%	1.0%	-0.2%	0.1%	1.5%	1.4%	0.1%	-0.6%	-0.1%	0.1%
58	1.6%	1.8%	1.8%	2.4%	1.6%	1.9%	0.5%	1.2%	0.0%	-0.8%	0.6%	1.0%	0.2%	-0.3%	0.3%	0.5%
62	1.6%	2.1%	1.9%	2.7%	2.0%	2.4%	0.3%	1.1%	0.6%	0.7%	1.5%	1.6%	0.4%	0.2%	0.4%	0.5%
66	2.7%	2.3%	1.9%	2.8%	1.3%	2.1%	0.2%	0.6%	0.0%	0.4%	1.4%	2.1%	1.5%	1.1%	1.1%	0.9%
70	1.8%	1.9%	2.1%	3.2%	1.5%	2.3%	0.7%	1.3%	0.4%	1.1%	2.1%	2.9%	2.2%	1.3%	1.0%	0.8%
74	0.9%	1.1%	1.6%	2.6%	1.8%	2.1%	0.7%	1.4%	0.6%	1.4%	2.1%	2.9%	2.2%	1.9%	1.7%	1.5%
78	0.7%	1.0%	1.9%	2.8%	1.7%	2.5%	1.1%	1.6%	0.8%	1.5%	2.5%	3.0%	1.9%	2.1%	2.0%	1.7%
82	0.0%	1.1%	1.5%	2.8%	2.5%	3.4%	2.3%	2.6%	1.3%	1.8%	2.8%	3.1%	2.1%	2.2%	2.3%	1.7%
86	0.3%	1.4%	1.4%	2.2%	2.0%	3.2%	2.1%	2.3%	1.3%	2.4%	2.8%	2.9%	2.2%	1.8%	1.8%	1.7%
90	0.5%	1.5%	0.9%	1.8%	1.9%	2.9%	1.6%	1.9%	1.6%	2.2%	2.7%	2.6%	2.2%	1.9%	1.7%	1.2%
94	0.2%	0.9%	0.4%	1.0%	1.4%	2.5%	0.8%	1.8%	1.9%	2.6%	3.2%	3.0%	2.5%	2.1%	2.0%	1.8%
98	0.3%	0.9%	0.4%	1.2%	1.3%	2.6%	1.1%	1.7%	1.6%	2.5%	3.0%	3.1%	2.2%	2.1%	2.2%	1.9%
102	-0.1%	0.7%	0.4%	1.3%	1.8%	3.0%	1.5%	1.9%	1.6%	2.5%	2.9%	2.8%	1.5%	1.3%	1.4%	1.2%
106	-1.0%	-0.1%	0.1%	1.0%	1.6%	3.2%	1.5%	1.5%	1.3%	2.4%	2.9%	2.6%	1.4%	1.4%	1.6%	1.3%
110	-1.4%	-0.6%	-0.3%	0.7%	1.1%	2.5%	1.1%	1.2%	0.9%	2.0%	2.7%	2.5%	1.3%	0.9%	1.2%	0.9%
114	-1.0%	-0.3%	-0.2%	0.8%	1.1%	2.7%	1.3%	1.3%	1.0%	2.0%	2.7%	2.7%	1.5%	1.3%	1.5%	0.9%
118	-1.2%	-0.6%	-0.4%	0.6%	1.0%	2.7%	1.4%	1.3%	0.8%	1.8%	2.8%	3.0%	1.4%	1.3%	1.5%	1.0%
122	-1.1%	-0.3%	0.0%	0.9%	1.2%	2.5%	1.7%	1.6%	0.7%	1.8%	2.8%	3.1%	1.5%	1.4%	1.4%	1.2%
126	-2.2%	-1.0%	-0.4%	0.7%	0.7%	2.1%	0.9%	0.9%	0.6%	1.7%	2.5%	3.0%	1.4%	1.4%	1.5%	1.4%
130	-2.1%	-1.0%	-0.7%	0.7%	0.8%	1.9%	0.9%	0.8%	0.6%	2.1%	2.8%	2.8%	1.3%	1.3%	1.3%	0.8%
134	-1.9%	-1.2%	-0.9%	0.0%	0.0%	1.2%	0.3%	0.5%	0.4%	1.8%	1.9%	2.2%	1.1%	1.4%	1.4%	1.1%
138	-1.5%	-0.7%	-0.7%	0.2%	0.5%	1.5%	0.4%	0.5%	0.4%	1.6%	1.8%	2.0%	1.1%	1.4%	1.4%	0.9%
142	-1.2%	-0.5%	-0.4%	0.2%	0.4%	1.2%	0.5%	0.6%	0.4%	1.4%	1.8%	2.1%	1.1%	1.5%	1.6%	1.3%
146	-0.9%	-0.3%	-0.5%	0.3%	0.3%	1.1%	0.3%	0.3%	0.4%	1.4%	1.5%	1.7%	0.4%	1.2%	1.4%	1.1%
150	-0.3%	0.1%	-0.2%	0.5%	0.6%	1.3%	0.4%	0.1%	0.3%	1.6%	1.6%	1.6%	0.2%	0.8%	1.1%	1.0%
154	0.0%	0.3%	0.3%	1.1%	0.9%	1.8%	0.8%	0.4%	0.4%	1.8%	1.9%	1.9%	0.5%	0.9%	0.8%	0.7%
158	0.2%	0.8%	0.5%	1.1%	1.0%	1.7%	0.8%	0.7%	0.5%	1.7%	2.1%	1.9%	0.7%	0.9%	0.6%	0.4%
162	0.1%	0.4%	0.4%	1.3%	1.1%	1.7%	1.2%	1.1%	0.8%	1.9%	2.0%	2.0%	0.8%	1.2%	0.9%	0.8%
166	0.4%	0.3%	0.6%	1.6%	1.6%	1.8%	1.2%	1.0%	1.0%	2.2%	2.1%	2.3%	1.0%	1.1%	0.9%	0.8%
170	0.4%	0.5%	0.5%	1.6%	1.5%	1.7%	1.1%	0.8%	1.0%	2.1%	2.2%	2.2%	0.8%	1.0%	0.7%	0.7%
174	0.4%	0.5%	0.6%	1.9%	1.8%	2.0%	1.4%	1.2%	1.3%	2.4%	2.4%	2.4%	1.0%	1.2%	0.9%	0.7%
178	0.4%	0.7%	0.4%	1.6%	1.4%	2.0%	1.4%	0.9%	1.0%	2.2%	2.2%	2.1%	1.2%	1.5%	1.0%	0.7%
182	0.7%	1.0%	0.7%	1.5%	1.4%	1.6%	1.2%	1.0%	1.1%	2.1%	2.0%	2.0%	1.2%	1.4%	1.0%	0.9%
186	0.7%	1.0%	0.9%	1.7%	1.4%	1.7%	1.0%	0.7%	0.8%	1.7%	1.8%	2.0%	1.2%	1.5%	1.1%	1.1%
190	1.0%	1.0%	0.8%	1.8%	1.5%	1.7%	1.1%	0.9%	1.0%	2.1%	2.2%	2.3%	1.2%	1.3%	0.8%	0.6%
194	0.6%	0.8%	0.9%	1.8%	1.4%	1.8%	1.1%	0.9%	1.2%	2.3%	2.6%	2.6%	1.6%	1.5%	1.0%	0.8%
198	1.3%	1.3%	1.1%	1.9%	1.5%	1.8%	1.1%	0.9%	1.1%	2.1%	2.4%	2.5%	1.8%	1.8%	1.2%	0.9%
202	1.9%	1.8%	1.4%	2.1%	1.5%	1.8%	1.2%	1.0%	1.2%	2.2%	2.3%	2.5%	1.7%	1.6%	1.1%	0.9%
206	2.0%	1.9%	1.5%	2.1%	1.7%	1.9%	1.0%	0.9%	1.0%	1.9%	2.0%	2.4%	1.6%	1.6%	1.1%	1.1%
210	1.9%	2.0%	1.6%	2.3%	1.9%	1.8%	0.9%	0.8%	1.0%	2.0%	2.0%	2.3%	1.6%	1.7%	1.2%	1.0%
214	1.9%	1.9%	1.5%	2.1%	1.9%	2.1%	1.2%	1.0%	1.1%	2.1%	2.1%	2.3%	1.5%	1.3%	0.9%	0.7%
218	1.7%	2.4%	1.9%	2.3%	2.2%	2.3%	1.5%	1.0%	1.1%	2.2%	2.2%	2.4%	1.7%	1.4%	0.8%	0.7%
222	1.8%	2.6%	2.0%	2.4%	2.2%	2.6%	1.6%	1.2%	1.3%	2.6%	2.4%	2.6%	1.9%	1.7%	1.1%	1.0%
226	1.8%	2.4%	1.8%	2.4%	2.2%	2.5%	1.8%	1.1%	1.3%	2.2%	2.3%	2.5%	1.7%	1.6%	1.1%	1.1%
230	2.1%	2.6%	2.4%	2.8%	2.5%	2.8%	2.1%	1.5%	1.6%	2.6%	2.5%	2.7%	1.7%	1.7%	1.3%	1.3%
234	2.2%	2.7%	2.5%	2.7%	2.5%	2.7%	2.1%	1.5%	1.5%	2.6%	2.7%	2.8%	1.7%	2.0%	1.4%	1.3%
238	2.3%	2.8%	2.6%	3.0%	2.7%	3.1%	2.3%	1.4%	1.5%	2.6%	2.7%	2.8%	1.9%	1.8%	1.4%	1.3%
242	2.3%	2.6%	2.3%	2.8%	2.5%	3.0%	2.2%	1.4%	1.6%	2.7%	2.6%	2.7%	1.8%	1.9%	1.4%	1.2%
246	2.7%	3.1%	2.3%	3.0%	2.7%	3.2%	2.5%	1.7%	1.7%	2.6%	2.5%	2.5%	1.6%	1.7%	1.2%	1.1%
250	3.0%	3.2%	2.4%	3.1%	2.9%	3.0%	2.6%	1.6%	1.8%	2.5%	2.5%	2.7%	1.7%	1.9%	1.4%	1.4%
254	2.9%	3.1%	2.7%	3.1%	2.8%	3.0%	2.6%	1.7%	1.8%	2.6%	2.6%	2.7%	1.6%	1.7%	1.1%	1.1%
258	3.1%	3.2%	2.7%	3.2%	2.9%	3.0%	2.7%	1.8%	1.7%	2.3%	2.4%	2.4%	1.3%	1.3%	0.8%	0.9%

Panel C: Nonreportables

	Sentiment index threshold															
Hold. Per.	**1.00**	**0.98**	**0.96**	**0.94**	**0.92**	**0.90**	**0.88**	**0.86**	**0.84**	**0.82**	**0.80**	**0.78**	**0.76**	**0.74**	**0.72**	**0.70**
30	-7.4%	-4.4%	-3.2%	-6.5%	-5.6%	-5.0%	-2.8%	-2.9%	-0.7%	-0.4%	-1.2%	-1.0%	-3.3%	-3.8%	-1.3%	-1.4%
34	-9.2%	-4.1%	-3.5%	-6.7%	-5.9%	-7.2%	-2.3%	-3.2%	-0.4%	-0.6%	0.7%	1.0%	-1.2%	-1.5%	-0.7%	-0.9%
38	-11.3%	-4.8%	-5.1%	-6.6%	-6.8%	-6.3%	-2.5%	-3.6%	0.1%	-0.9%	0.3%	0.5%	-0.6%	-1.1%	-0.3%	-0.4%
42	-10.9%	-6.5%	-6.5%	-8.1%	-8.5%	-7.1%	-3.7%	-4.5%	-0.5%	-1.2%	0.2%	0.3%	-1.0%	-0.9%	0.3%	-0.2%
46	-10.2%	-7.2%	-6.4%	-8.1%	-8.3%	-6.4%	-3.1%	-4.7%	-1.9%	-1.6%	-0.7%	-0.3%	-1.7%	-2.1%	-1.1%	-1.3%
50	-10.7%	-7.8%	-6.1%	-7.0%	-7.3%	-6.4%	-3.6%	-5.1%	-2.4%	-2.0%	-1.0%	-1.0%	-2.1%	-2.2%	-1.4%	-1.2%
54	-11.1%	-9.0%	-6.9%	-7.9%	-6.9%	-5.7%	-3.3%	-4.3%	-1.5%	-2.4%	-1.8%	-1.8%	-2.6%	-2.3%	-1.7%	-1.5%
58	-10.5%	-10.0%	-8.0%	-8.2%	-6.4%	-5.0%	-2.6%	-3.6%	-0.9%	-2.0%	-1.2%	-1.1%	-1.8%	-1.6%	-1.1%	-1.2%
62	-11.1%	-10.1%	-7.8%	-8.6%	-7.4%	-5.8%	-3.0%	-3.3%	0.2%	-2.0%	-0.9%	-1.3%	-2.6%	-1.9%	-1.5%	-1.8%
66	-9.4%	-9.0%	-6.8%	-7.7%	-6.9%	-5.1%	-2.8%	-3.2%	-0.5%	-2.4%	-1.2%	-1.0%	-2.1%	-2.2%	-1.9%	-2.1%
70	-9.4%	-8.9%	-6.7%	-6.6%	-5.3%	-4.9%	-2.9%	-3.2%	-0.4%	-2.2%	-1.2%	-1.4%	-2.6%	-2.4%	-2.4%	-2.5%
74	-9.3%	-8.2%	-6.1%	-5.7%	-4.7%	-4.8%	-3.2%	-3.6%	-0.7%	-2.1%	-1.0%	-0.8%	-1.6%	-1.8%	-2.1%	-2.0%
78	-9.1%	-7.8%	-5.9%	-5.3%	-4.0%	-3.6%	-1.9%	-2.6%	-0.2%	-1.7%	-0.9%	-0.3%	-1.2%	-1.1%	-1.4%	-1.5%
82	-8.6%	-7.1%	-5.0%	-4.5%	-3.4%	-2.7%	-1.6%	-2.4%	0.3%	-1.4%	-0.6%	-0.2%	-1.0%	-0.9%	-1.4%	-2.0%
86	-8.5%	-7.2%	-5.3%	-4.4%	-3.4%	-2.7%	-1.7%	-2.8%	0.0%	-1.1%	-0.3%	-0.2%	-0.8%	-1.0%	-1.7%	-2.3%
90	-8.7%	-7.4%	-5.5%	-5.1%	-4.3%	-3.5%	-2.2%	-2.7%	-0.2%	-1.2%	-0.7%	-0.4%	-0.3%	-1.0%	-1.6%	-2.2%
94	-8.2%	-7.1%	-4.9%	-4.7%	-3.7%	-3.0%	-2.1%	-2.3%	-0.2%	-1.1%	-0.8%	-0.3%	-0.6%	-1.0%	-1.6%	-2.0%
98	-8.4%	-7.6%	-5.4%	-5.0%	-3.7%	-2.8%	-1.7%	-1.6%	0.1%	-0.6%	-0.1%	0.2%	-0.5%	-0.8%	-2.1%	-2.2%
102	-7.3%	-6.7%	-5.4%	-5.3%	-3.7%	-2.5%	-1.4%	-1.4%	0.2%	-0.9%	-0.5%	0.0%	-0.8%	-1.3%	-2.1%	-2.4%
106	-8.1%	-7.4%	-6.1%	-5.5%	-4.2%	-3.2%	-2.4%	-2.1%	0.0%	-0.3%	-0.4%	0.0%	-0.4%	-1.0%	-2.1%	-2.4%
110	-7.1%	-6.5%	-5.2%	-5.3%	-4.0%	-3.8%	-3.0%	-3.0%	-0.8%	-1.5%	-1.2%	-0.4%	-0.7%	-1.3%	-2.2%	-2.4%
114	-7.1%	-6.5%	-5.1%	-4.8%	-3.5%	-3.0%	-2.5%	-2.8%	-1.3%	-1.8%	-1.4%	-0.7%	-0.9%	-1.1%	-1.7%	-2.3%
118	-7.0%	-6.1%	-4.8%	-4.7%	-3.3%	-2.7%	-2.1%	-2.3%	-1.2%	-1.6%	-1.3%	-0.7%	-0.8%	-1.1%	-1.7%	-2.0%
122	-6.4%	-5.8%	-4.5%	-4.0%	-2.8%	-2.3%	-2.0%	-2.3%	-1.3%	-1.4%	-0.9%	-0.4%	-0.6%	-0.5%	-1.2%	-1.7%
126	-6.1%	-5.9%	-4.5%	-4.1%	-2.8%	-2.0%	-1.6%	-2.0%	-0.9%	-1.1%	-0.6%	-0.5%	-0.6%	-0.7%	-1.2%	-1.7%
130	-6.3%	-5.8%	-4.5%	-4.2%	-3.1%	-2.5%	-1.9%	-2.3%	-1.1%	-1.7%	-1.0%	-0.7%	-0.8%	-0.8%	-1.3%	-1.7%
134	-6.5%	-5.5%	-4.4%	-4.3%	-3.0%	-2.1%	-1.7%	-1.9%	-0.9%	-1.7%	-1.0%	-0.7%	-0.7%	-0.8%	-1.0%	-1.4%
138	-6.1%	-5.0%	-3.5%	-3.8%	-2.6%	-1.5%	-1.0%	-1.7%	-0.8%	-1.8%	-1.0%	-0.4%	-0.1%	-0.5%	-0.8%	-1.2%
142	-5.9%	-4.6%	-3.4%	-3.7%	-2.5%	-1.6%	-0.8%	-1.7%	-0.9%	-1.6%	-1.2%	-0.7%	-0.4%	-0.5%	-0.7%	-0.9%
146	-5.8%	-4.8%	-3.5%	-3.5%	-2.1%	-1.2%	-0.4%	-1.6%	-0.8%	-1.6%	-1.1%	-0.7%	-0.2%	-0.6%	-0.9%	-1.1%
150	-5.6%	-5.0%	-3.6%	-3.6%	-2.4%	-1.5%	-0.8%	-1.7%	-1.1%	-2.0%	-1.4%	-0.8%	-0.4%	-0.8%	-1.0%	-1.0%
154	-5.5%	-5.1%	-3.7%	-3.4%	-2.1%	-1.4%	-0.7%	-1.6%	-1.2%	-1.9%	-1.5%	-1.1%	-0.6%	-0.7%	-0.8%	-0.9%
158	-4.7%	-5.0%	-3.8%	-3.5%	-2.4%	-1.6%	-1.1%	-1.7%	-1.1%	-1.9%	-1.6%	-1.1%	-0.7%	-1.2%	-1.0%	-1.1%
162	-4.6%	-4.6%	-3.4%	-3.6%	-2.5%	-1.7%	-0.8%	-1.4%	-0.8%	-1.5%	-1.1%	-0.9%	-0.5%	-1.1%	-1.0%	-1.3%
166	-4.6%	-4.8%	-3.5%	-3.6%	-2.6%	-1.8%	-0.9%	-1.6%	-0.8%	-1.4%	-1.0%	-0.5%	-0.1%	-0.7%	-0.7%	-1.1%
170	-5.0%	-4.8%	-3.4%	-3.7%	-2.6%	-2.0%	-1.1%	-1.6%	-0.7%	-1.3%	-0.9%	-0.6%	0.0%	-0.5%	-0.6%	-1.0%
174	-4.9%	-4.9%	-3.6%	-3.7%	-2.7%	-2.1%	-1.1%	-1.6%	-0.8%	-1.3%	-0.8%	-0.4%	0.2%	-0.2%	-0.3%	-0.7%
178	-4.8%	-4.8%	-3.4%	-3.9%	-2.8%	-2.1%	-1.0%	-1.7%	-1.0%	-1.4%	-1.1%	-0.5%	0.0%	-0.6%	-0.4%	-0.8%
182	-4.6%	-5.1%	-3.7%	-4.2%	-2.7%	-1.9%	-1.0%	-1.6%	-1.0%	-1.5%	-1.1%	-0.4%	0.2%	-0.3%	-0.2%	-0.7%
186	-4.2%	-4.7%	-3.5%	-3.7%	-2.6%	-1.7%	-1.1%	-1.4%	-0.9%	-1.5%	-1.1%	-0.3%	0.4%	-0.2%	-0.2%	-0.7%
190	-3.9%	-4.6%	-3.4%	-3.8%	-2.5%	-1.6%	-1.0%	-1.4%	-1.0%	-1.5%	-1.0%	-0.2%	0.4%	-0.3%	-0.4%	-0.9%
194	-4.4%	-4.8%	-4.0%	-4.2%	-2.8%	-1.8%	-1.1%	-1.4%	-0.9%	-1.3%	-0.8%	-0.1%	0.4%	-0.2%	-0.3%	-0.6%
198	-3.6%	-4.3%	-3.3%	-3.9%	-2.5%	-1.6%	-1.1%	-1.4%	-0.8%	-1.1%	-0.8%	-0.2%	0.5%	-0.2%	-0.2%	-0.7%
202	-3.8%	-4.4%	-3.6%	-3.9%	-2.4%	-1.4%	-1.0%	-1.4%	-0.8%	-1.2%	-0.9%	-0.3%	0.4%	-0.2%	-0.3%	-0.7%
206	-3.3%	-3.9%	-3.4%	-4.0%	-2.5%	-1.7%	-1.1%	-1.2%	-0.8%	-1.1%	-0.8%	-0.1%	0.4%	-0.3%	-0.3%	-0.7%
210	-3.4%	-3.7%	-3.3%	-3.9%	-2.6%	-1.5%	-1.0%	-1.4%	-0.8%	-1.1%	-0.8%	0.2%	0.6%	-0.1%	-0.1%	-0.7%
214	-3.5%	-4.0%	-3.4%	-4.0%	-2.8%	-1.7%	-1.0%	-1.3%	-0.9%	-1.3%	-1.1%	0.0%	0.6%	-0.1%	-0.1%	-0.6%
218	-3.4%	-3.8%	-3.1%	-3.8%	-2.6%	-1.5%	-0.9%	-1.2%	-0.9%	-1.3%	-1.1%	-0.2%	0.3%	-0.3%	-0.3%	-0.7%
222	-3.5%	-3.8%	-3.0%	-3.7%	-2.4%	-1.1%	-0.6%	-0.9%	-0.7%	-1.1%	-0.8%	0.3%	0.6%	-0.2%	-0.2%	-0.7%
226	-3.5%	-3.9%	-2.8%	-3.7%	-2.5%	-1.2%	-0.6%	-1.1%	-0.7%	-1.2%	-0.8%	0.4%	0.5%	-0.2%	-0.2%	-0.5%
230	-3.2%	-3.7%	-2.6%	-3.7%	-2.9%	-1.5%	-0.7%	-1.2%	-0.8%	-1.3%	-0.8%	0.4%	0.5%	0.1%	-0.1%	-0.6%
234	-3.0%	-3.5%	-2.7%	-3.5%	-2.5%	-1.2%	-0.4%	-0.6%	-0.3%	-0.9%	-0.6%	0.4%	0.6%	0.1%	-0.2%	-0.4%
238	-2.9%	-3.2%	-2.4%	-3.6%	-2.6%	-1.3%	-0.5%	-0.6%	-0.3%	-0.7%	-0.4%	0.4%	0.6%	0.1%	-0.2%	-0.5%
242	-2.8%	-3.1%	-2.3%	-3.6%	-2.8%	-1.4%	-0.5%	-0.4%	-0.2%	-0.7%	-0.4%	0.4%	0.6%	0.1%	-0.1%	-0.5%
246	-2.4%	-2.8%	-2.0%	-3.3%	-2.9%	-1.4%	-0.3%	-0.4%	-0.1%	-0.7%	-0.2%	0.6%	0.7%	0.1%	-0.1%	-0.6%
250	-2.6%	-2.7%	-2.0%	-3.3%	-2.6%	-1.0%	-0.2%	-0.2%	-0.1%	-0.5%	-0.2%	0.6%	0.6%	0.1%	0.0%	-0.5%
254	-2.7%	-3.0%	-2.1%	-3.4%	-2.7%	-1.1%	-0.2%	-0.3%	0.0%	-0.2%	0.1%	0.8%	0.9%	0.5%	0.3%	-0.2%
258	-2.3%	-3.0%	-2.2%	-3.3%	-2.7%	-0.9%	-0.1%	-0.1%	0.2%	-0.1%	0.3%	1.0%	1.0%	0.6%	0.4%	0.0%

Declaration of authorship

I hereby declare

- that I have written this thesis without any help from others and without the use of documents and aids other than those stated above,
- that I have mentioned all used sources and that I have cited them correctly according to established academic citation rules,
- that I shall not pass on any copies of this thesis to any third parties without the President's consent, with the exception of fellow students or persons who have provided me with essential information for this thesis, to whom I may pass on copies of this thesis after the procedure has been concluded.

St. Gallen, November 10th, 2007

Michael Mähr