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Commodity Market Investments and Behavioral Finance: The Case of Coffee
Can Simple Trading Strategies Generate Excess Returns in the Arabica Futures Market?

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Abstract

In this thesis I test for whether strategies that are constructed to exploit possible price patterns that are created by cognitive biases described by behavioral finance are able to earn excess returns in the Arabica futures market over the period between January of 1990 and December of 2013. The cognitive biases include the disposition effect described by Kahneman and Tversky (1979), representativness by Kahneman and Tversky (1974), overconfidence by Hilary and Menzly (2006), the endowment effect by Kahneman, Knetsch and Thaler (1991) and general market sentiment. To test whether these cognitive biases have a significant effect on the market I have constructed strategies based on technical analysis which is built to exploit the assumptions from behavioral finance. While some of the strategies are able to earn statistically greater returns than both long-only and T-Bills in different sub periods none are able to consequentially earn greater returns throughout all periods. However, the trend following strategy with two 5 day moving averages outperform the long only strategy in both periods, 1990 to 2001 and 2002 to 2013. There is in my mind not enough evidence in this study to support the belief that strategies based on technical analysis can generate statistically significant returns.

Sammendrag

I denne masteroppgaven tester jeg om strategier som er konstruert for å utnytte eventuelle prismønstre som blir skapt av kognitive svikter, som blir beskrevet i adferdsfinans, er i stand til å oppnå en meravkastning i futuresmarkedet for Arabica-kaffe i perioden fra januar 1990 til og med desember 2013. De kognitive bristene inkluderer disposisjonseffekten beskrevet av Kahneman and Tversky (1979), representativitet av Kahneman and Tversky (1974), overdreven selvtillit av Hilary and Menzly (2006), the endowment-effekten av Kahneman, Knetsch and Thaler (1991) og generell markedsstemning. For å teste om disse kognitive sviktene gir signifikante utslag i markedet har jeg konstruert strategier som er basert på teknisk analyse som igjen er bygget for å utnytte antakelsene fra adferdsfinans. Noen av strategiene er i stand til å tjene statistisk signifikante avkastninger i forhold til T-Bills og long-only i ulike underperioder er ingen i stand til tjeme signifikant bedre i begge periodene. Men den trendfølgende strategien med to fem-dagers bevegende gjennomsnitt presterer bedre enn long-only i begge periodene, 1990 til 2001 og 2002 til 2013. Jeg mener jeg ikke finner tilstrekkelig med bevis i denne studien til å støtte troen på at strategier basert på teknisk analyse er i stand til generere statistisk signifikant avkastning.

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1 Introduction

In this thesis I analyze whether cognitive biases in the market actors described by behavioral finance create exploitable price patterns in the futures contract on the coffee type Arabica. I will investigate if trading in the market for coffee futures with strategies built on technical analysis can earn above normal returns. Several studies have drawn the rationality of the market actors into question. Among these the study by Kahneman and Tversky (1979) are probably among the most ground-breaking. Kahneman and Tversky present an alternative model for how people makes decisions under risk called the prospect theory. They claim the expected utility theory describes how people should choose were they perfectly rational, and not how they actually choose.

The profitability of trading strategies in futures trading is a heavily disputed subject. During the last couple of decades several studies have been published showing that, assuming that their findings are correct, that it is possible to earn above normal returns through relative uncomplicated trading strategies in the commodity futures market. One of the most influential studies in the field was published by Gorton and Rouwenhorst (2006). By creating an equally-weighted index of commodity futures returns over the period between 1959 and 2004 they showed that they could achieve a return that was similar to equities, had negative correlation with the returns of both equities and bonds, and had a positive correlation with inflation. Szakmary, Shen and Sharma (2010) implemented trend-following strategies in the commodities futures markets which yielded excess return in 22 of the 28 markets they tested. Another article by Miffre and Rallis (2007) investigates whether commodity futures prices show signs of short-term continuation and long-term reversal. They tested the price drift with momentum strategies and price reversion with contrarian strategies, and found that the momentum strategies generated an average 9.38% return per year, while the contrarian strategies did not work.

These findings reveal that there are opportunities for increased profit and diversification by investing in the commodity market. The critics of these studies claim the findings is a result of statistical miscalculation, insufficient inclusion of transaction costs, or making other assumptions in their trades that will not hold up in the real world.

The studies have mainly had a broad focus with a large portfolio of commodities, and they have tested one or two types of strategies with monthly data dating back to the 70s. This article also examines the profitability of trading strategies, but I will focus on investments in the Arabica coffee futures traded at ICE. I will investigate if focusing on one commodity will produce greater returns than an average of several commodities. It will also allow a more in depth investigation into different trading strategies. While earlier studies have focused on one or two strategies at a time I will look at a greater number, making it possible to compare different strategies against each other. The trading strategies have been constructed on the basis of, and tested out on historical prices from the period 1990-2013. Additionally I will use daily intervals, and not monthly as in most of the earlier studies. This allows me to see if there is possible to earn greater returns when you monitor the market more closely on a day to day basis. Additionally, this might be more relevant to the traders who hold positions for a shorter periods than one month.

The strategies that has been created in this thesis are based on technical analysis which has the theoretical background from behavioral finance. The main premise of behavioral finance is that people, or the market actors are only rational in a limited sense, contrary to the perfectly rational agent from classical economic theories. In this article I examine the returns of several systematic trading strategies in Arabica coffee futures. The strategies are constructed to earn returns from eventual mean reversion, trending and momentum, and include strategies based on support and resistance, relative strength index, and moving averages. The strategies operate on a day to day basis. The support and resistance strategy is a contrarian strategy. It is based on the belief that earlier price highs and lows constitute a sort of price ceiling and floor which the price usually stays between. The strategy goes short when the price reaches the resistance or ceiling, and goes long when the price declines to the support or price floor. The strategies based on Relative Strength Index (RSI), and moving averages tries to identify trends or momentum, buying when prices have been increasing and selling when they have declined, expecting that the price will continue in the same direction.

To evaluate the profitability of the trading strategies they will be tested against a passive long-only strategy, and 3 month US Treasury Bills as the risk free rate. To make sure that the trading strategies are not just profitable in certain market conditions or specific periods of time I will examine the profitability in two sub periods, 1990-2001 and 2002-2013. These periods start at moments events occurred that might have been market changing. The collapse of the coffee cartel in 1990 and the introduction of better processing technology in the early 2000`s that allowed the big roasters to put more Robusta in their instant blends.

Before I start the analysis of the different trading strategies I will review of earlier studies on the profitability of trading strategies in chapter 2. Then in chapter 3 I have a review of coffee as a commodity and the market for coffee. In chapter 4 go through the basic mechanics of the commodities futures marked. As behavioral finance is the basis of technical analysis I will go through some of the fundamental concepts of that theoretical strand of economics before I tackle technical analysis with the different trading strategies and their rationale in chapter 6. The remainder of this thesis is organized as follows: Chapter 7 covers the coffee futures contract for Arabica Coffee "C" with descriptive statistics. Then in chapter 8 I will go through the specific buy and sell signals for the different strategies before I report the results obtained. The last chapter contains concluding remarks and suggestions for further research.

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2 Behavioural Finance and Price Systematics

The field of finance has created several useful tools for investors which can help them obtain the highest amount of expected return for whatever level of risk they are willing to accept.(Modern Portfolio Theory) Pricing models that help value securities such as CAPM and Arbitrage Pricing Theory, and give insights into expected risks and returns. All this financial theory is based upon the Efficient Market Hypothesis which makes several assumptions about the market and its actors. The following is among the most central assumptions: people make rational decisions, they are unbiased in their predictions about the future, and the price reflects all available information. The assumptions regarding the rationality and unbiasedness of people have been rejected by psychologists for a long time. Many studies have shown that humans have tendencies to act irrationally. The incorporation of psychology and that disciplines view on human reasoning, into economy has led to a new branch in the field of economy called behavioral economics. It is difficult to define the start of a new approach or field, but a lot started to happen in the 70`s. From behavioral economics came behavioral finance which acknowledges man's cognitive shortcomings, and tries to unravel what effect they may have on the market. Most of the studies that have been conducted in this field is on the stock market. You could argue that the traders in the commodity futures market is more professional and skilled, but the biases have been detected among professional traders as well as in the general public. I will investigate if it possible to connect pricing in the futures market for coffee to theories of behavioral economics.

One of the more influential contributions to the field of behavioral finance was made by Thaler (1980). He argued that the traditional theories in economics are based on a normative view of the consumer. It is based on a rational model of how they should choose, and assumes that this is how they do choose. And that this assumption leads to systematically incorrect predictions about human behavior. Thaler calls for an approach

[1] *In this thesis I use the term "return" to refer to the change in the price of the futures contract and the performance of the trading strategies. This is a bit improper as it is not strictly return I am talking about. In the case of the price change in the futures contract it is the natural logarithmic change from day to day. And in the case of the trading strategies there is no investing of cash, as you do not buy the futures contract, but post a margin such that the clearing house can be certain you have enough cash to cover eventual losses. The margin is also redeemed to the trader including accrued interest and losses or profits when the position is closed.*

that is more descriptive in a sense that it describes what a consumer actually would do, this is what the field of behavioral economics is trying to do.

2.1.1 Overconfidence

When investors have experienced some success in the market they tend to become overconfident. The self-attribution bias is when people attribute their success to skill while their failure is caused by bad luck or external events beyond their control. This contributes to the overconfidence as people downplay their failures and exaggerates their skill. According to psychologists overconfident people overestimate their knowledge, underestimate risks, and exaggerate their control over events. In a study Hilary and Menzly (2006) find that after analysts have had a series of good estimates, they follow up with a period of predictions that are less accurate than the average and deviate from other analysts. Additionally several studies have found that overconfidence leads to excessive trading. Among these studies are Barber and Odean (2000) who found that overconfidence leads to excessive trading, and that this increased trading frequency leads to lower returns. In another study Statman, Thorley and Vorkink (2006) studied stock market returns and trading volumes over 40 years and found that months with high returns are followed by months with higher trading volume. On the other hand, months with low returns are followed by months with lower trading activity. According to Odean (1998b) trader overconfidence may lead to underreaction to news, which may lead to the returns becoming positively serially correlated, or "to trend" in plain English. Odean also states that overconfidence may lead to overreaction to news which can lead to negative serial correlation in the returns, or price reversion. He says that whether the market over- or underreacts depends on the nature of the news: *"The degree of this under- or overreaction depends on the fraction of all traders who under- or overweight the information. A review of the psychology literature on inference finds that people systematically underweight abstract, statistical, and highly relevant information, and overweight salient, anecdotal, and extreme information."*

2.1.2 Disposition Effect

Kahneman and Tversky (1979) criticized expected utility theory, and developed a an alternative model for decision making under risk which they called *prospect theory*. They found that people have varying preferences for risk taking. Their main finding was that people generally show risk aversion in choices involving sure gains, and risk seeking behavior in choices involving sure losses. When people were faced with two options involving a gamble or a sure thing, with the same expected value, $500 for sure or 50% chance at $1,000, most people choose 500$ for sure. But when the options were turned into losses, a loss of $500 or 50% chance of losing $1,000 people tended to choose the gamble. If the respondents where rational and answered in line with the expected utility theory, whether it was a gain or a loss should not affect the risk aversion. The conclusion was that people value losses higher than they value gains. Shefrin and Statman (1985) adapted this behavior to the investor to investigate which effect it has on trading patterns. They found that it led the investors into a predisposition to sell winners too early and selling losers too late. Seeking pride and avoiding regret, they named this the *disposition effect*. The theory is that selling a stock with a gain triggers a feeling of pride, but people put of realizing losses by selling a stock that has declined in value as this would trigger a feeling of regret. Selling winners too soon and losers too late implies that the winning stocks would continue to do well while the losers will continue to do bad. Odean (1998a) found out that this was true. On average in his data set a loser that was held performed 1 percent below the market the following year, while the sold winners outperformed the market with 2.4 percent on average. He calculated that if you include tax savings resulting from selling the loser, the total return of the investor`s would be improved by 4.4 percent if they sold the losers and held on to the winners. The seeking of pride and fear of regret thus reduce the wealth of investors in two ways: earning lower returns when they sell winners too soon and losers too late, and investors are paying more tax than necessary because of the same. Their behavior contradicts the assumption that people try to maximize their wealth. An important question here is whether a large group of investors suffering from the disposition effect can influence the market. Findings in a study by Frazzini (2006) suggest that it does. When there is positive news regarding a firm this leads a positive development of the stock price, but as the price increases people sell this winner. The capitalizing of these gains temporarily depress the stock price from fully incorporating the new information. This underreaction to positive news results in a predictable positive price drift. When investors try to avoid regret and ride losers for too long negative news results in a negative price drift on low volume as people are hesitant to realize their losses. In the futures market things are not that clear cut, as the same news may be good to some and bad to others. If there for instance is news of too little rainfall in Brazils main coffee region which can, if the situation continues, lead to drought and a big decrease in the crop size. This would lead to much higher coffee prices. If you are long in the coffee market this is good news, but if you are short this is bad news. The effect of the disposition effect would therefore be twofold in the futures market, working on both the short and the long side. In the drought scenario the actors on the long side would experience a price increase and close out their positions capitalizing their gains, while the short side holds on to their positions hoping to win back what is lost. This way both sides in the market would contribute to a positive price drift. When the price is going down, maybe due to news of rain the dry coffee regions, the roles would change between long and short and there would be a negative price drift.

2.1.3 Representativeness

According to psychological research the human mind takes shortcuts to reduce complexity when processing new information. While reducing mental strain these shortcuts may lead people to make inaccurate conclusions. One of these cognitive shortcuts is called representativeness, Kahneman and Tversky (1974) define this as a deviation from objective to subjective probability, meaning that people tend to make judgement based on stereotypes or prejudices. An example of an outcome of this bias was made by Shefrin (2002) who showed that people tend to see good companies as good investments. This is a conclusion made by a shortcut, the stock may well be overpriced even if it is in a good company. Bondt and Thaler (1985) found that this may lead to a popularity for good firms that drive the prices higher and higher. Eventually it becomes apparent that investors have been too optimistic causing a reversion in the stock prices. This can be seen as an overreaction to good news. One might think that it seems hard to defend both over- and underreactions in the market, but a short term underreaction and long term overreaction is not incompatible. If stocks of good companies, or "glamour" stocks show tendencies of reversion, is unpopular stocks in firms with minimal growth then underpriced? Lakonishok, Shleifer and Vishny (1994) using the stocks at the New York Stock Exchange and American Stock Exchange they put the 10 percent stocks with highest growth into a group called glamour stocks, whereas the firms with the lowest growth were value stocks. They found that the average return over the next year was 11.4 percent for the glamour stocks, and 18.7 percent for the value stocks. Additionally De Bondt (1993) found that, what he calls non-experts tend to believe that apparent price trends will continue, making them optimistic in bull markets and pessimistic in bear markets. Can this be translated to the coffee futures market? There is of course no glamour stocks in the futures market for coffee, as the contracts are not on companies but a standardized commodity. However, you might argue that certain commodities can become "glamour commodities". If there is news of a rust leaf outbreak in Colombia and the price is starting to climb. Then it becomes a common held belief that coffee futures generally generates good return which again causes people to flood in on the long side in the market, causing an overreaction to the news. Then when the real effect of the rust leaf outbreak becomes known the price reverts down to the intrinsic value, causing a negative price drift.

2.1.4 Market sentiment

In traditional financial theory it is assumed that people make rational decisions that considers risk and uncertainty to maximize their wealth, it is assumed that in the question of money cold logic would trump emotion and psychological biases. Is this so, or may emotion overpower reason also in the question of maximizing your wealth? Several studies suggest that the latter is the case.

In a study Loewenstein, Weber, Hsee and Welch (2001) draw on research from different sub-fields of psychology to investigate how decision making in risky situations can be affected by emotions. Their main focus is on how fear influences decisions. Their findings suggests that people evaluate risk at two levels, both cognitively and emotionally, and that their risk-as-feelings hypothesis can explain several phenomena that cannot be explained by theories based on rational behavior. Even though the cognitive evaluations of risk are in line with decision theory regarding probabilities and how desirable the outcome is and the emotional reaction is affected by the cognitive process, emotions can arise from very little cognitive activity and override the final decision. Especially fear reactions can arise from very little stimulus, resulting in decisions that are dominated by emotional reactions and not reason. Decisions that are made in complex and uncertain situations, are according to the authors, prone to be more influenced by emotions.

Nofsinger (2005), bases his article on the belief that financial decisions are influenced by emotions and mood. Optimism and pessimism is transmitted through social interaction leading to a general mood in the population. He then argues that this causes financial decision makers to be affected by the general level of optimism and pessimism in society, which in turn will influence their decisions in a correlated fashion. When the mood is increasing it causes optimism, happiness and hope. This leads to a change in behavior including taking greater risks and more trading. Emotions that at the peak becomes extreme in the form of euphoria, overconfidence and excess. Decreasing mood leads to pessimism, which results in declining stock prices, people taking less risk and lower spending. He argues that it is these factors that cause the formation of bubbles with the consequent busts.

Those who do not believe that investor sentiment influence market prices argue that rational and rich investors would act as arbitrageurs and exploit the mispricing created by the emotional traders. However this requires the stocks to be correctly valued. Therefore Baker and Wurgler (2006) suggest that the effect from sentiment would be most noticeable in stocks that are hard to value. They find that the stocks of firms that are hard to value tend to be undervalued when sentiment is low, and when sentiment shifts up and become high, this reverses and the same stocks tend to deliver high returns. In months of high measured sentiment stocks of small firms earn on average a return of 0.73 percent the month after. When sentiments were low one month the return the following month was an average 2.37 percent. This large difference in returns was not registered in stocks of large firms, which suggest that optimistic traders drove the stock price to be overpriced.

The decisions made by investors that benefits them best in the long run is usually made void of emotion. Shefrin and Thaler (1977) outline human beings that is a constant conflict between a farsighted planner and a shortsighted doer. They see this inherent conflict in individuals as a problem regarding intertemporal choice being an assumption in economic theory. Intertemporal choice describes a situation where an individual's decisions affect future options, if saving today will increase your consumption in the future this is what a farsighted rational agent would do. Problems occur when people have problems with self-control and the myopic doer makes the decisions and not the planner. The authors compares this conflict of interest between the planner and the doer with the agent/principal problem, where the doer is the short sighted and egoistic employee, and the planner as the employer.

The capitalization of commodities in the 2006-2008 period which is was described among others by Tang and Xiong (2012), may be attributed to market sentiment. Meaning that rising prices in one market leads to optimism that spills over into unrelated markets. And as mentioned earlier fear is the most powerful drive for decisions made on the basis of feelings, causing panic in the stock market from plummeting prices to spill over into the coffee market.

Herding is an expression that is used in the financial markets when a significant group of investors trade in the same direction for some time. Prechter Jr (2001) states that human herding behavior is result of impulsive mental activity triggered by the signals of others. It originates in a part of the brain that handles most of our emotions, the limbic system. When people are in an emotional state that part of the brain typically works faster than the part that handles rational thought processes. Primitive thought processes that leads to something like instinctive actions can be appropriate in life threatening situations, but in the financial markets. And Prechter Jr claims he found evidence of herding in data on large groups of financial professionals. He found because stress increases impulsive behavior which leads to failure, and the failure increases more stress, creating a negative feedback loop. This leads to herd behavior, which the author claims is extremely difficult to avoid by clinging on to rational independence in group settings. Smith, Suchanek and Williams (1988) conducted experiments in the form of laboratory market simulations on people with economic background. Even though they all received perfect knowledge on coming dividend prospects, they produced boom-and-bust market profiles. After several simulations on the same subjects the market bubbles disappeared. The conclusion drawn from this were that bubbles and crashes would be much more unlikely if the same traders were in the market the entire time. However, as Bishop (1987) state, novices always enter the market, and experienced people retire, additionally Prechter shows that people have much more of their money invested in the stock market at the peaks than at the bottom, meaning that inexperienced traders cause an influx of money in boom periods, and a strong withdrawal in bust periods. This would lead to positive feedback investing as the rising prices would cause an influx of money into the market, the increasing demand would lead to rising prices. When prices are falling people would withdraw their money, causing a further drop in prices.

Nofsinger and Sias (1999) studied both individual and institutional investors in regards to herding and feedback trading. Their analyzes show a strong positive correlation between changes in returns and institutional ownership on an annual basis. The top ten per cent of shares with increasing institutional ownership experienced a 31 per cent better return than the top decile of shares that had the greatest decrease in institutional ownership. According to the authors this result probably stems from the institutional investors engaging in positive feedback investing in a larger degree than individual investors or that institutional investors' herding exerts a greater influence on prices than herding of individual investors. However, the analysis they performed does not indicate that the institutional herding behavior was irrational as there was no evidence of return reversal in the two years after the herding period. On the contrary, shares bought by institutional investors were found to outperform those that were sold.

Most of the studies on herding and market sentiment is performed on the stock market which has a much larger share of unprofessional traders, while the commodity futures markets are characterized by a high degree of professionalism. This may mute the effect of feelings and herding as drives for trading activity. The effects of herding and emotion on trading behavior have however also been found in people with economic background, which makes it plausible that they can be found in the futures market as well. If this is the case, the general mood in the market may lead to euphoria or dysphoria that could lead to booms with prices rising too high and then busts with prices falling too low, and then with prices reversing back towards the intrinsic value. This would manifest with short term price drift and long term price reversion.

2.1.5 The Endowment Effect

Another concept within behavioral finance is the endowment effect. Kahneman, Knetsch and Thaler (1991) found that the price people required for an item once it was in their possession was far higher than what they were willing to pay before ownership was established. The preference and the utility of the group changed after they gained ownership over an object, in the researchers case a mug. This is what they called the endowment effect and is not consistent the assumptions of constant utility and preferences. The endowment effect was later linked to loss-aversion. If someone owns an object, the person considers the pain of losing it, when he does not own it he considers the pleasure of getting it. However, List (2003) showed that the endowment effect can be eliminated by market experience. It is hypothesized that professional traders view the objects they trade as merely a proxy for the money they can make out of it. If the endowment effect is affecting traders in the market this causes people to hold on to the investments they are already holding. This would prevent, or slow the pace at which the price adjusts to new information which falls under the category of underreaction leading to price drift.

The field of behavioral economics is extensive and I have only discussed a part of it. It is however quite clear that human beings are not the paragons of reason that some traditional economic theories seem to suggest. As Thaler (2000) points out, behavioral economics is changing the view of humans in economics, from the completely rational and self-interested homo economicus into one closer to the flawed homo sapiens. Behavioral finance faces a lot of criticism, where the most central is that the "quasi-rational" in the market would be exploited by the fully rational who would take all their money. The "quasi-rational" would have to either learn or they would become irrelevant in the market. However, empiric studies show that this is not necessarily the case. An example of this is the study by De Long, Shleifer, Summers and Waldmann (1990) that show that the "quasi-rational" or "noise traders", as they are often called in financial circles, can be able to earn higher expected returns. The authors ascribe this to the fact that "noise traders" create a risk in the prices that prevent the rational traders to arbitrage against them, making it possible for the price to diverge greatly from the fundamental values. As John Maynard Keynes allegedly said: "*The market can remain irrational longer than you can remain solvent.*" Additionally the "noise traders" can increase their returns by inadvertently bearing much risk. Another criticism is that behavioral finance contradicts itself, and the effects can be highly situational. There is also little guidance or suggestions to how the mispricing caused by the rational biases can be exploited. Difficulties arise when it comes to incorporating the psychological phenomena that leads to irrationality into the theory and models of economy. Even though if we accept that market actors are quasi-rational, it is not given that the quasi-rational traders create patterns that are recognizable and possible to exploit to earn excess returns. The effects are hard to quantify especially as they are situational, and the changes would lead to a great increase in complexity of the theory which would decrease its usability.

3 Empirical Testing of Behavioral Finance: Technical Analysis

Technical analysis is built on the theory and assumptions of behavioral finance and I will use technical analysis to test. In this chapter I will go through the basic principles of technical analysis, and what the rationale behind it is. Then I will explain how technical analysis can be used to generate trading strategies I will use later on to exploit the patterns technical analysis is meant to reveal.

There are two main "schools" for how to make investment decisions in finance: fundamental and technical analysis. If you use fundamental analysis in the futures market you attempt to find the intrinsic value of a contract by examining all factors you believe can affect its value. The goal is to find a value you believe to be the correct value with which you can compare the actual price in the market. If the analysis leads you to believe the commodity future is under- or overpriced you take position accordingly. Technical analysts, often called technicians, only consider the price movement in the market, and the data pertaining to the price movements, such as trade volumes. They believe that the supply and demand in the market can reveal which direction the price will go next. Technical analysis is based on three main assumptions, the first is that the market discounts everything, meaning that at any time the price of good or derivative reflects everything that affects the price. Therefore, following a technician's rationale there is no use in looking at the fundamentals as they are already priced in and you could not possibly know everything. And if you somehow possess all fundamental information you still have to assess the psychological aspect of the market actors. The second assumption is that prices tend to follow trends. Implicating that when a trend has been established the market price is more likely to move in the same direction as the trend rather than against it. The last assumption is that history is prone to repeat itself. Technicians attribute this to market psychology; or more precisely that the market participants tend to react the same way to the same stimulus. As many of the strategies that originates from technical analysis are based on assumptions from behavioral finance, those strategies become a possible way to test the theories from behavioral finance empirically. If the strategies that are built to exploit inefficiencies that are caused by irrationality are found to generate excess return, this would lend great support to the theories of behavioral finance.

Later I will construct systematic strategies to send buy and sell signals when certain conditions relating to the price and price movements occur. In this chapter I will explain the rationale behind these strategies, and how they work on a general basis. A more detailed description of what will instigate buy and sell signals in the various trading strategies will be presented in chapter 8.

3.1 The Different Trading Strategies and Their Theoretical Foundation

The main reasons for why strategies based on technical analysis may work can be found in behavioral finance. As the data technical analysts use is historical data, analyzing them cannot, according to the efficient market hypothesis, lead to positive returns. Technical analysis is a broad field with many different theories about price systematics. In this article I will only discuss three, which might be the most central in the field of technical analysis. These three can also be connected to the effects discussed in the chapter on behavioral finance.

3.1.1 The Trend, a Result of Underreaction?

The trend is maybe the most important concept in technical analysis. A trend is merely the general direction in which a market is heading, whether it is upwards, downwards or sideways. The idea of the trend probably originates from Charles H. Dow when he wrote a series of *Wall Street Journal* editorials in the period 1900-1902. The belief is that when you are in a trend the price changes tend to be in the same direction as the trend. There are several theories for why the market may display visible trends which stems from limited rationality from the market actors. Underreaction to news is one the reasons for why we may see price drift in the market, and is caused by cognitive biases such as overconfidence, the disposition effect, market sentiment and herding, and the endowment effect. Frazzini (2006) found that both positive and negative news travels slowly, and that this generates a price drift. If the market price does not adjust instantly to news, it does not reflect all available information. When the market price takes days to absorb new information trend or momentum will occur as the price moves to reflect all information. Another cause for trend or momentum in market prices is positive feedback investing. This happens when there is investors who buy when prices are rising and sell when they are falling. If a sufficient amount of traders feedback trade, this herd mentality may lead to further market declines or increases, and is capable of moving the prices away from the fundamentals. The traditional view dating back to at least Friedman (1953) is that rational investors stabilize prices, because when they see prices moving away from the fundamentals they will take opposite positions bringing the price back towards the intrinsic value. But more recent research by e.g. Long, Shleifer, Summers and Waldmann (1990) indicate that risk aversion may keep rational speculators from taking large positions opposite of the market trend, preventing this reversion. Positive feedback investing may cause trading strategies that tries to ride the trend or momentum to have positive return. If rational investors brings the price back against the fundamental value this may cause contrarian strategies to earn positive returns. It should be mentioned that the price of commodity futures contracts converge on the spot at the contract settlement. This means that the price of a futures contract cannot wander too far off from its intrinsic value as may be the case with equities.

The strategies I will apply to exploit a possible trend or momentum caused by underreaction to news are crossover strategies with moving averages for the trend, and a strategy based on an oscillator called the relative strength index (RSI) for the momentum.

Many of the methods in technical analysis tries to recognize the trend. Once you think you have identified a trend you will want to ride the trend, going long if it is an upward trend, or going short if it is a downward trend. It is common to try and identify trends using moving averages. A moving average (MA) is just the average of prices over the last days and is a smoothing of the price movements. By using one short run MA (SRma) and one long run MA (LRma) you can interpret situations where the SRma crosses the LRma going up as a change into a uptrend which instigates a buy signal. When the opposite happens and the SRma crosses the LRma going down this can be interpreted as a change into a downtrend which instigates a sell signal.

Momentum is a Latin word and is an expression pertaining to the speed and mass at which an object moves. In the financial markets it is an expression that is connected to the force and uniformity of a price movement. If the price rises or sinks much and fast and with small corrections during the period we say that the momentum is high. If on the other hand the price changes are small, and does not rise or sink on longer term we say the momentum is weak. Even though if there is a clear uptrend the momentum may be weak, as we will see in the following figure.

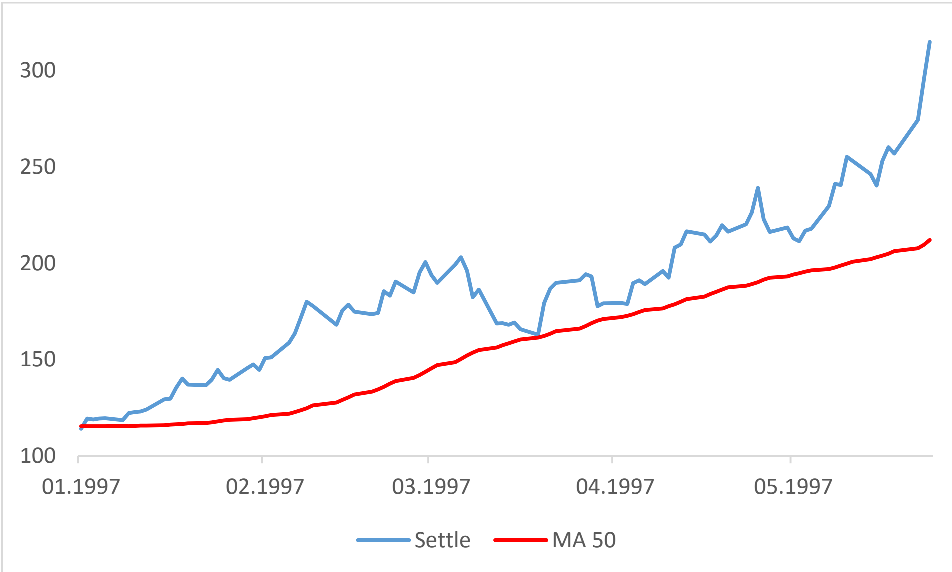

Figure 1: Settle price and 50 day moving average during the 1997 price peak.

In Figure 1 we can see the trend illustrated by the 50 day moving average is clearly up from February and onwards. However between March and April the price loses momentum.

There are several methods for measuring the momentum, we will focus on oscillators and RSI which stands for Relative Strength Index. It was first introduced by J. Welles Wilder in the late eighties. It is meant to say something of the own strength of an equity, but will in this thesis be applied on futures. RSI indicates the relationship between appreciation and depreciation over the last few days. It is calculated as the sum of price changes on days with appreciation multiplied with 100, and divided with the sum of price changes on days with depreciation plus price changes on days with appreciation measured over a specified amount of days. RSI moves on a scale from 0 to 100, but extreme values below 10 and above 90 are rare. The length of the period which you base the RSI on depends on the horizon of the investment. A longer RSI period will give a slower moving RSI and therefore less buy and sell signals. RSI is used as a momentum indicator, where the idea is to buy high and sell higher. The RSI also have a tendency to turn before the price does. Using the RSI as a momentum indicator I will buy when it rises above a certain level. I have then interpreted the rising RSI as upward momentum. Then I hold the long position until the RSI falls below 70 again, interpreting that as a probable change in trend. Correspondingly I could then sell if RSI falls below 30, and exit when it rises above 30 again. The levels at which the RSI generate buy/sell signals are up for personal evaluation. In the figure below we can see the price and the RSI movement over an arbitrary period of time, with 70, 30 and 50 RSI hurdles. The RSI is on the left axis, and price on the right.

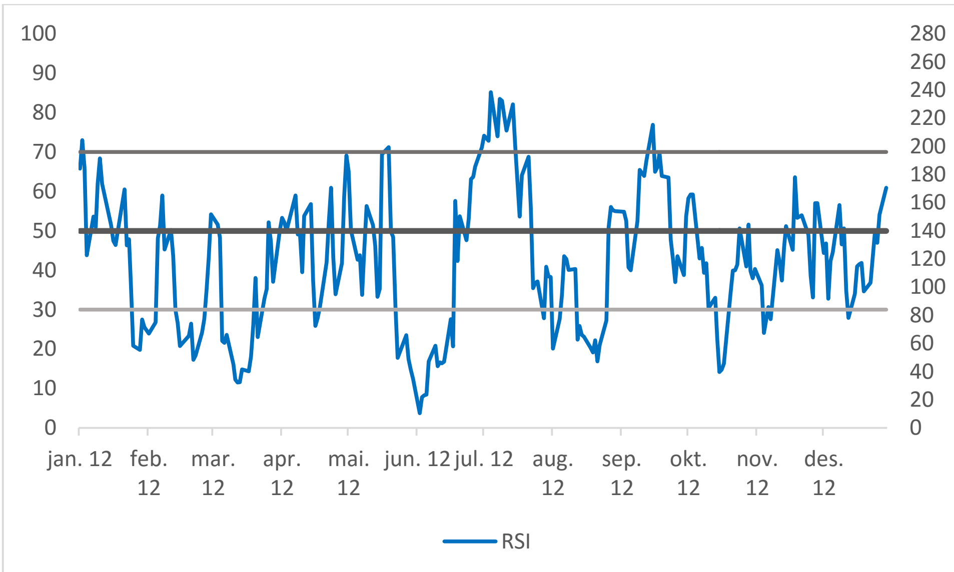

Figure 2: Relative Strength Index and Price for the year 2012.

Figure 2 displays the price and the RSI with hurdles at 70 for strong upward momentum, 30 for strong downwards momentum, and 50 as the neutral value. As we can see the RSI shows a tendency to over- or undershoot the hurdles. In the figure there is also possible to see a tendency that price rises after the RSI have crossed 70 going upwards and sinks after the RSI has gone below 30. I will examine if this is an actual tendency that is possible to exploit or not.

3.1.2 Trading on Price Reversion with Support and Resistance

For exploitation of the price reversion caused by overreaction to news which may result from the cognitive biases known as representativeness, overconfidence or herding, a strategy with support and resistance levels are used. The following strategy tries to exploit possible contrarian movements in the price by trading on support and resistance levels. According to technical analysis these are levels that the prices often bounces back off. Resistance are levels where the prices allegedly often stop in an upward trend, and support are levels where the price often stops in a downward trend. When the price breaks through the resistance, the resistance often becomes the new support. If the price goes below the support, that support level often becomes a new resistance. There are several factors that contribute to this phenomena. According to Linløkken and Frölich (2010): Resistance occurs when most of the actors that have bought finds out the level is sufficiently high enough to sell. Reasons for this may be that the price were at the same level earlier and then it fell, and people expect the same to happen again. Many investors went long in this future at this level earlier and wish to sell now to avoid losses. Investors that sold at this level earlier but in the meantime has bought in at lower levels want to sell at similar prices as last time because it was a good trade earlier. There may also be some big actors that sees this price level as too high and wish to exit at this level if there is an opportunity to do so. There is a surplus of sellers around resistance levels. This surplus will usually be sufficient to push the price down again. If the price on the other hand breaks through this means that the sellers have sold, and there is still actors that wish to buy. After a break out there is often a sharp increase in the price.

Support arises in a falling rate when the majority of the market considers the price to be attractively low, and starts buying again. There may be new buyers that did not get to buy the last time the prices were this low, and now sees an opportunity to get in. It may be speculators that bought in the last time the price were this low and made a profit in the meantime. They see a new opportunity for profit. Big actors may perceive the price as cheap and accumulate futures at the support level. Overall there will be a surplus of buyers that will support the price at this level, such that the price usually will start rising again. If the support breaks, all the buyers have bought and there are still sellers left and the price will keep on falling. To base buy/sell decisions on support and resistance, you buy when you reach support and sell when you reach resistance. As well as attempting to catch the price reversion the support and resistance strategy acknowledges that prices do not necessarily revert. This is incorporated into the strategy by sending buy or sell signals when the price breaks through the support or resistance. Buy signals when the resistance is broken and sell signals when the support is broken.

4 Previous Studies on Commodity Market Investments

Over the last three decades there has been published several significant works on the profitability and diversification effects of investing in commodity futures. This chapter is a survey of the most important results reported in scientific journals on trading strategies in the commodities futures market. They are grouped by their main findings, and at the end of this section there is a table displaying several articles, their methods and findings.

Several studies have investigated the efficiency of the commodities futures markets. The most influential article on the commodity futures market in recent years is probably "*Facts and Fantasies About Commodity Futures*" by Gorton and Rouwenhorst (2006). They showed that commodity futures historically have offered the same risk-return relationship as equities, negative correlation with return on equity and bonds, and positive correlation with inflation. Allegedly their findings resulted in a great influx of capital into the commodities markets. Table 1 is from their study, and we can see that commodity futures actually has earned a larger Sharpe ratio than stocks in the period of their analysis. The t-statistic reported is the confidence that the average risk premium is different from zero.

Table 1: Risk Premium of Commodity Futures from Gorton and Rouwenhorst (2006), from the period 1959-2004

	Commodity Futures	**Stocks**	**Bonds**
Average	5.23	5.65	2.22
Standard Deviation	12.10	14.85	8.47
T-statistic	2.92	2.57	1.77
Sharpe ratio	0.43	0.38	0.26
% returns >0	55	57	54

Source: Gorton and Rouwenhorst (2006)

The study was performed by constructing an equally-weighted fully-collateralized index of commodity futures containing 36 different commodities. They have based their study on monthly data in the period between 1959 and 2004. To compute the performance index they invest 1$ in each commodity futures contract at the beginning of the first month, and at the same time invest the same amount in T-bills to collateralize the index fully. At the end of each month, the positions in the different contracts are rebalanced to equal weights, such that they have an equal amount of dollars invested in each commodity again. The index that Gorton and Rouwenhorst constructed has as they mention an embedded trading strategy. When they rebalance at the end of the month they effectively buy a portion of the commodities that went down in price, and sell a portion of the ones that went up in price. This is a contrarian strategy, and if the prices tend to overreact in each direction before they revert back you effectively buy future winners and sell future losers. This would lead to better performance compared to the buy-and-hold method. During the period 1959-2004 Gorton and Rouwenhorst's index generated an excess return of 5% over T-bills per annum. When we look at specific commodities they range from propane as the best performing with a 20.61% annual geometric return to electricity as the worst performing at -54.56%. Coffee earned an annual geometric return of 7.68%.

As can be seen in Table 2 which is an excerpt from Gorton and Rouwenhorst (2006), there is a great difference between returns on spot commodity prices and collateralized futures returns. The return on buy-and-hold spot return at 3.47% per annum has actually been outpaced by inflation at 4.13

Table 2: Geometric Average Annualized Returns to Spot Commodities and Collateralized Commodity Futures, from the period 1959-2004

	Rebalancing		
Index	Monthly	Annual	Buy and hold
Futures	9.98	11.18	10.31
Spot	7.66	6.66	3.47
Inflation	4.13		

Source: Gorton and Rouwenhorst (2006)

Even though G&R found that commodity futures has delivered the same risk-return relationships as equities over the entire period 1959-2004, there is great variations between different periods. As we can see in Figure 3 taken from the paper by G&R commodity futures outperformed stocks in the 70s, but that this was reversed in the 90s.

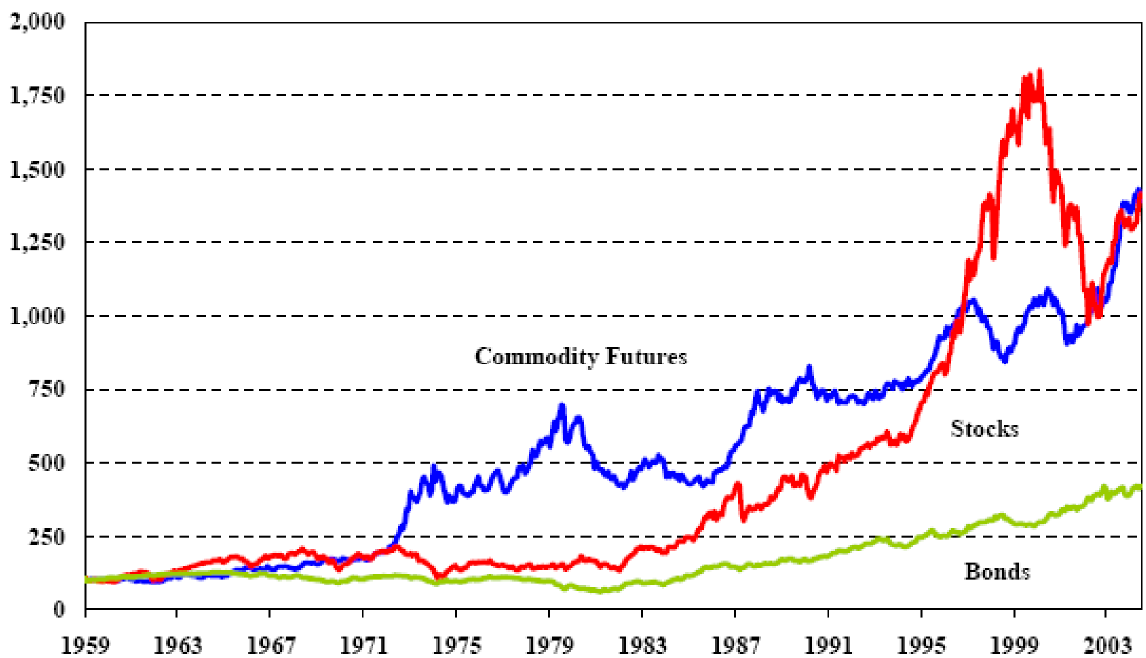

Figure 3: Stocks, Bonds, and Commodity Futures Inflation Adjusted Performance 1959/7-2004/12

Source: Gorton and Rouwenhorst (2006)

The findings of Gorton and Rouwenhorst contributed to a newfound enthusiasm for commodity futures which led to large investors such as pension and index funds to pour billions of dollars into the commodity futures market. This is the shared view of many, among them Tang and Xiong (2012) who conclude that the rapid growth of index investments in commodity markets coincide with non-energy commodities becoming more correlated with oil prices, financial assets and other commodities. They claim that this reveals a financialization of commodities markets, which help explain the simultaneous boom and bust of several commodities with different fundamentals. Tang and Xiong also speculate that this financialization will persist as long as commodity indices stay popular among financial investors. In another study by Hamilton and Wu (2015) the authors reason that if purchases by commodity index funds influence futures prices, then the relative positions of these index investors should help predict excess returns in these contracts. They found nothing that could cause them to conclude that commodity index funds positions can help predict returns.

Several studies show that naively holding long positions does not generate positive abnormal returns, among them are Aulerich, Irwin and Garcia (2011). They wanted to test the theory of normal backwardation by examining the existence of a risk premium in futures markets to determine if the hedgers pay speculators to reduce their price risk. The data they used is from the period 2000 to 2009, and covers 12 commodity futures markets. By analyzing the returns of Commodity Index Traders(CITs) they found that CITs hold net long positions opposite commercial traders who hold consistent short positions, while the positions of the noncommercial traders fluctuate between net short and net long. According to the theory of normal backwardation, as the CITs hold positions opposite of the hedgers (commercial traders) they should earn a positive risk premium. They found that for the entire period the CITs experienced losses in 9 out of 12 commodities markets with net aggregate losses of -$6.9 billion. On that basis they rejected the theory of normal backwardation.

Main, Irwin, Sanders and Smith (2013) wanted to find out why returns to commodity index investments, contrary to the alleged diversifying benefits and equity-like returns, have had such disappointing real world returns. They found that the negative returns are not due to contango as the returns to long-only positions are not determined by term structure, but largely driven by the same risk premium present in spot prices. They also show that the performance of the commodity futures tend not to change when markets change from contango to backwardation. Another explanation of the poor performance is that the financialization of the futures markets has led to a systematic decline in risk premiums. They found that the energy markets generally had a clear decline in risk premiums in the mid-2000s, while the non-energy markets on the other hand experienced an increase in risk premiums. In total they concluded that there is not sufficient evidence to support a theory of a systematic decline in risk premiums from the mid-2000s onwards. They do not conclude on why returns have been disappointing, but claim that the evidence from their study suggests expected return from long positions in the commodity futures markets being approximately equal to zero.

Ten years after their influential article, Bhardwaj, Gorton and Rouwenhorst (2015) reviewed their findings in a follow up study. The average commodity risk premium of their equally weighted index was 5.23% per annum in the in-sample (1959-2004) and in the 3.67% the out-of-sample (2005-2014). This difference is not big enough to be statistically different, hence they conclude that their earlier findings largely hold up out-of-sample. When it comes to the diversification effect from commodity futures they find that the correlation to other assets increased during the financial crises, effectively diminishing diversification. However this increase in correlation was only temporary.

In a study Narayan, Ahmed and Narayan (2014) found that momentum-based trading strategies could yield statistically significant profits. By applying a set of moving average trading rules, 19 commodities futures were ranked each month in the period March 1983 to October 2012. They used short-run moving averages(SRma) and long-run moving averages (LRma) of the monthly commodities returns and subtracted the LRma from the SRma to create a ranking. The commodity with the largest positive difference received ranking 1, and so on down to rank 19. On the basis of this ranking they created 5 different strategies with different weighting on different ranking commodities and with or without shorting. The portfolios they constructed of the different trading strategies earned returns ranging from 7.6-8.6% per annum. They also show that the opportunity to short-sell led to greater profits. When they tested the same strategies with daily data they only had a portfolio return of around 4.8% per annum, of which they find limited evidence is statistically significant.

By combining momentum and term structure signals Fuertes, Miffre and Rallis (2010) showed that by creating a double-sort strategy combining momentum and term structure signals were able to achieve an abnormal return of 21%. The article expands on works by Miffre and Rallis (2007) and Jegadeesh and Titman (1993) who showed momentum strategies could be profitable and the term structure signals from Gorton and Rouwenhorst (2006) and Erb and Harvey (2006). Miffre and Rallis identified 13 momentum strategies that generated an average return of 9.38% per year, Jegadeesh and Titman found that buying past winners and selling past losers with a holding period of 6 months realized an excess return of 12.01% per year on average. Furthermore Erb and Harvey found that an equally weighted annually rebalanced portfolio had an excess return of 10.95% in the 1993-2003 period. Fuertes, Miffre and Rallis had the following methodology: At the end of each month they ranked the commodities on the basis of their roll return. Using that ranking they divided the commodities into three groups, Low, Med, High. Then they sorted each of these groups into two portfolios, Winner and Loser, based on their return over the last R months (R ranging from 1-12 months). The strategy then was to go long the High-Winner portfolio and short the Low-Loser portfolio. On average, the portfolios of this strategy earned 21.32% per annum.

The article by Dewally, Ederington and Fernando (2013) provide evidence that profits in the commodity futures market is dependent on the hedging pressure. They found that mean return for hedgers are negative, and mean return for speculators are positive, and that traders that hold positions opposite to the majority of hedgers earn higher profits than the ones that hold positions in accordance with most of the hedgers.

Additionally their findings indicate that commodity futures momentum is merely futures price converging on the spot price, due to hedging pressure.

Szakmary et al. (2010) used dual moving average crossover (DMAC) and channel rules with different parameterization and found that it gave positive profits in 22 of 28 markets in the whole period of 48 years and in most sub periods. With the DMAC there is a long signal when the short-term moving average unit value (STMA) exceeds the long-term moving average value (LTMA) and a short position when STMA<LTMA. With the channel strategy a long position is entered if the price at the end of the month exceeds the highest price over the previous *N* months, a short position is entered if the end of month price is lower than the lowest price registered over the previous *N* months. The various DMAC strategies earned monthly excess returns ranging from 0.53% to 0.78%, while the different channel strategies earned monthly excess returns ranging from 0.71%-1.14% for the entire sample period. All of which are statistically significant.

In a study by Scott H. Irwin, Carl R. Zulauf and Jackson (1996) data on several agricultural commodity futures with sample period 1975 to 1992 was used to exanimate if the agricultural futures market show signs of mean reverting prices. They found that in accordance with several other studies asymptotic regression results give clear signs of mean reversion in commodity futures prices. Additionally they did a Monte Carlo regression analysis, which lends no support for mean reversion in commodity futures prices. These conflicting findings are contributed to the fact that the sample size is too small to make any assumptions about the asymptotic distribution of the sample. Assumptions that needs to be met to ensure a reliable regression result.

Table 3: List of studies on trading strategy profitability with main findings

Authors	**Year**	**Title**	**Publication**	**Method**	**Main findings**
Bhardwaj, Gorton and Rouwenhorst	2015	Facts and Fantasies About Commodity Futures Ten Years Later	Yale ICF Working Paper	Long only, with contrarian rebalancing.	Supports original findings, but acknowledge increasing correlation with other asset classes during the financial crisis.
Narayan, Ahmed, Narayan	2014	Do Momentum-Based Trading Strategies Work in the Commodity Futures Markets?	Journal of Futures Markets	Momentum-based strategies, by short – and long-range moving averages.	Findings suggest that it is possible to earn statistically significant profits in the futures market.
Dewally, Ederington, Fernando	2013	Determinants of Trader Profits in Commodity Futures Markets	Review of Financial Studies	Analyzed hedgers and speculators profits.	Show that mean speculator profits are positive and mean hedger profits are negative.
Szakmary, Shen, Sharma	2010	Trend-following trading strategies in commodity futures: A re-examination	Journal of Banking & Finance	Trend-following trading strategies, monthly dataset spanning 48 years and 28 markets. Dual moving average crossover and channel strategies.	They show that all strategies they implemented earned positive profits in 22 of 28 markets. The returns prevail over most sub periods.
Fuertes, Miffre and Rallis	2010	Tactical allocation in commodity futures markets: Combining momentum and term structure signals	Journal of Banking & Finance	Combination of momentum and term structure signals.	Achieved an abnormal return of 21%
Miffre and Rallis	2007	Momentum strategies in commodity futures markets	Journal of Banking & Finance	Short-term momentum, long term contrarian strategies	Contrarian strategies does not work. 13 momentum strategies that generate 9.38% return a year.
Gorton and Rouwenhorst	2006	Facts and Fantasies About Commodity Futures	NBER WORKING PAPER SERIES	Long only, with contrarian rebalancing.	Same risk-return as equities, negative correlation with equities and bonds, positive correlation with inflation.
Erb and Harvey	2006	The Strategic and Tactical Value of Commodity Futures	Financial Analysts Journal	Momentum and term structure based strategies.	They found that the strategies had historical attractive returns.
Irwin, Zulauf and Jackson	1996	Monte Carlo Analysis of Mean Reversion in Commodity Futures Prices	American Journal of Agricultural Economics	Monte Carlo regression analysis	No support for mean reversion in commodity prices

5 The Coffee Market

5.1 Production

Coffee is produced in a tropic climate and Arabica has the best conditions at an altitude of between 1000 and 2500 meters above sea level. Where the mean temperature is around 21 degrees Celsius with great variations between day and night temperature. Coffee is being produced in more than 60 countries, with Brazil being the greatest by far, producing three times more than the second largest producer Columbia. There are two main types of coffee, Arabica and Robusta. Arabica stands for the greatest share of all coffees with 59% of the worlds totaled coffee production. Robusta is easier to produce, it is as the name implies more robust regarding both climate and diseases. Arabica is a delicate plant which is susceptible to diseases such as rust leaf, and vulnerable to both frost and drought. But Arabica is considered to hold a much higher quality which is reflected in the price. In the period 2001-2014 the average discount for Robusta over Arabica was 34%, the maximum discount was 69% . This inspires the big roasters to increase the share of Robusta in their blends, especially when the discount is high. The substitution effect helps dampen the price spikes in Arabica.

The numbers on production and trade have been gathered from a report by the International Coffee Organization(ICO)[2]. Total world production of Arabica in 2012/2013 was about 90 million 60 kg bags.

The coffee is produced in a belt around the equator, nevertheless the harvest period varies in the different regions. Brazil, as the largest producer by far, harvests their coffee between April and September, while other big coffee producing countries like Ethiopia and Colombia harvest October to December and October to March respectively. This means that harvest numbers are coming in year round, which may have large impact on prices if they diverge from expected crop size. Additionally this makes coffee a little different from other agricultural commodities that has one harvest period. For these commodities it is not uncommon to have rising prices up until the month of harvest, and then a sharp drop in futures price to the first contracts that settles after the harvest is finished. This is caused by the accumulated storage cost for the commodity which is highest the last month before the new crop comes in. As there is no single harvest month or period for coffee this pattern is not that clear.

[2] A report published by the ICO: "*World coffee trade (1963-2013): A review of the markets, challenges and opportunities facing the sector*".

5.2 Coffee Trade

Coffee is one of the most traded tropical commodities, usually called soft commodity or just Softs, in the world. Other tropical commodities or Softs are cocoa, sugar, and fruit. Coffee are measured and exported in 60 kg bags. According to the International Coffee Organization (ICO) 67.26 million bags of Arabica, and 43,35 million bags of Robusta were exported in the twelve months ending in May 2015.[3] As exporting countries has a small amount of own consumption, most of the coffee produced is exported. The trade of coffee mainly takes place between high income and low income countries. The commodity is usually produced in poor or developing countries and exported and consumed in rich industrialized countries. Green coffee can be stored for years without significant loss of quality, but roasted beans is considered fresh produce. Therefore coffee is generally imported to the consumption countries as green beans and then roasted there, most of the value added in the coffee value chain is added in the processing which takes place in countries close to the end consumer and not the producing countries. The fact that price paid for the green beans constitute so little of the end price to the consumer is part of the reason why the elasticity of demand is very low.

In 1990 the total amount of coffee exported was 81 million bags, in 2013 this had increased to 111 million bags. Robusta have stood for most of the growth with a mean annual increase by 2.7%, while Arabica has had an annual increase of 1.4%. It is Vietnams increase in production that constitutes most of the growth of Robusta exports.

USA is the greatest consumer of coffee with about 20% of the world consumption, the countries in the EU stands for about 65% of consumption. It is a steady increase in demand for coffee worldwide, with an average annual growth rate of 2.1% since 1990. The growth in the traditional importing markets, such as USA and Europe, has since 1990 had an average annual growth of only 0.7%. Consumption in the emerging markets have stood for most of the increase with an average annual growth rate of 4.7% from 1990 to 2012. This is mainly in Asian countries that historically are mostly tea drinkers, there has also been an increase in domestic consumption in the exporting nations, especially Brazil and Ethiopia. The big roaster, Kraft Foods, Nestlé, Procter & Gamble and Sara Lee stand for about 50% of the world's coffee processing. These big multinational corporations often have their own farms or buy in big quanta from long term partners. Most of the world's coffee is traded in bilateral agreements and the price paid can diverge greatly from what the spot price or futures price would suggest.

[3] (http://ico.org/monthly_coffee_trade_stats.asp?section=Statistics 10.07.2015

5.3 The Price History of Arabica 1990-2013

The main drivers of the coffee price is production, consumption and stock movements. Most of the value added to the coffee is after it is harvested, so the price of the green coffee is only a small fraction of the end price paid by the consumer. This paired with the fact that coffee constitutes a small amount of total spending for most consumers results in inelastic demand. Because of this the price of Arabica increases sharply when there is a deficit or expected deficit in production. We have seen examples of this several times since 1990 where weather that is unfavorable to crop size have led to extreme price increases.

The International Coffee Agreement (ICA) was signed in 1962. It was an agreement between the coffee-producing and -consuming nations which aim was to secure a stable and high price for the coffee. The ICA was managed by the International Coffee Organization (ICO) through export quotas. In 1989 the ICA collapsed when the agreements members could not agree on the quotas. Because the coffee market was regulated before 1990 I have chosen to focus on the period since. The following figure is an illustration of the price of the first position Arabica futures (KC1) from the period 1990 to 2013.

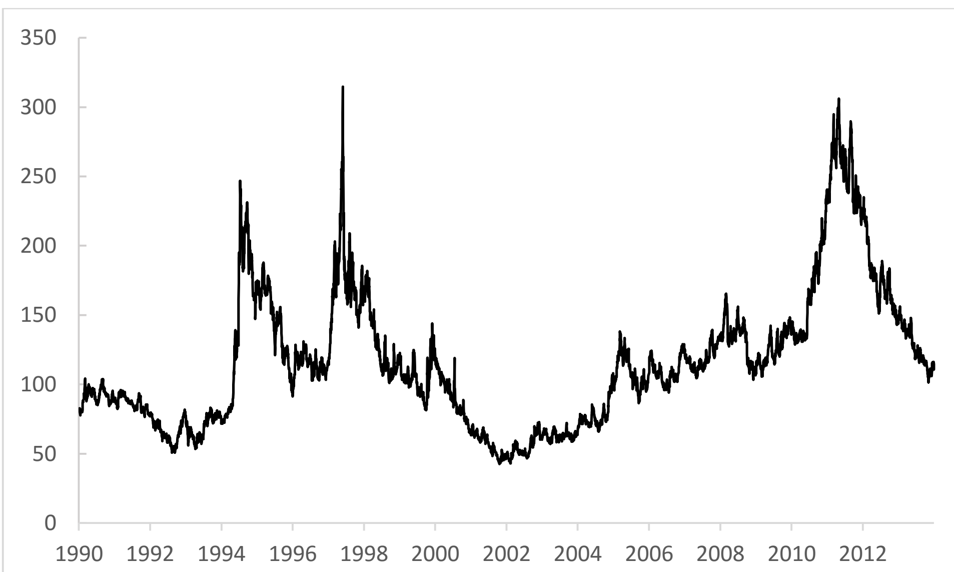

Figure 4: Price history of the first position (KC1) for Arabica futures contract 1990-2013, settle prices in cents/lb.

The Arabica price fell in the 90s, this was caused by the collapse of the ICA in 1989 coupled with Vietnam increasing their Robusta production by 1400% from 84 thousand tonnes in 1990 to 950 thousand tonnes in 2000. As can be seen in Figure 4, there are big gaps in the coffee price from lows of about 40 cents/lb. to highs of over 300 cents/lb. The three most extreme price spikes were seen in 1994, 1997 and 2011. In 1994 a frost hit Brazil's coffee growing districts hard which led to the price on the first position futures contract to increase from 84 cents/lb. in April to 245 cents/lb. in July. An price increase of 191% in two and a half month. The cause of the price spike in 1997 is a bit more complex. It is considered to be caused by mainly two factors. According to Frechette and Delavan (1998) the big coffee roasters started in 1997 with "Just In Time", which is a way to organize your operation where storage is reduced to a minimum. This means that you have to buy coffee in the spot market continually, increasing the uncertainty when it comes to securing a constant flow of supplies which can increase the price volatility. Additionally the weather phenomenon El Niño was happening which increases uncertainty especially in Latin-America. And the fear of failed crops pushed the price up about 164% in five months.

At the beginning of the 2000s the coffee price sank to historical lows and were for a period priced at under 50 cents/lb. The Vietnamese has gotten a lot of blame for the sinking prices as the Vietnamese government encouraged farmers to plant Robusta in a big scale. Another important reason for this was the development of better processing technology, which allowed the big coffee companies to put more Robusta in their instant coffee blends, reducing the bitter, harsher taste this cheap bean possess (Lewin, Giovannucci and Varangis (2004)).

In May 2011 the price of Arabica reached a record high since 1977 with 304,55 cents/lb. There were two main reasons for this high price, increasing demand from growing economies such as Russia, China, Brazil and Indonesia, coupled with La Nina which gave poor weather for coffee producers in Latin America. Moist weather provides good conditions for the coffee disease *Hemileia vastatrix,* commonly known as rust leaf. And Colombia experienced an rust leaf epidemic from 2008 to 2011. (Avelino, Cristancho, Georgiou, Imbach, Aguilar, Bornemann, Läderach, Anzueto, Hruska and Morales (2015))

6 The Basic Mechanics and Sources of Return in the Commodity Market

This chapter is an basic explanation of how the commodity futures marked works, and its main mechanism`s and concepts. From what a futures contract is, to the drivers of the futures contract price.

A commodity futures is a binding standardized contract to take or give delivery of an amount of the underlying commodity, with a standardized quality at a certain time and place, for a set price. For each contract there is one party who is committed to deliver and one party who is committed to take delivery.

The purpose of the futures market is to give the market participants the opportunity to lock in future prices. It is an insurance in case the market price moves against you. This is achieved by the transfer of risk. There are three main actors in the market. First we have the long hedgers who lock in their buy price, this group is made up of mainly companies who further refine the product before the sell it on to the end consumer. Second there are the short hedgers which is a group made up of the producers of the commodity, they want to lock in the sell price and wish to prevent any loss incurred due to falling prices. For simplicity "going long" will often be referred to as buying and "going short" as selling. The third group is the speculators. They do not handle the physical commodity, but they take on positions in the futures market expecting to make a profit from the changing commodity prices or risk premium. A commonly held view is that speculators play an important role by supplying the market with liquidity. However research performed among others by Kang, Rouwenhorst and Tang (2014) and Grossman and Miller (1988) indicate that speculators are momentum traders who consume liquidity and hedgers are market makers who supply liquidity with contrarian strategies. Additionally the futures market is a means for price discovery and the futures market enables the trading of commodities through different time periods, smoothing the prices through these different periods.

For every transaction there is at least three actors involved. The buy and sell orders are placed to a clearing house who finds a match with an offsetting offer. The clearinghouse acts as an insurance that the agreement will be met. To do this the clearing house requires a margin that is calculated on the basis of the volatility and the price of the underlying and is meant to cover any possible loss that may occur during one day. This is to ensure that the different parties are capable of meeting their obligations. With futures you do not buy a contract as it is with options, you merely post a margin with the clearinghouse as collateral which you will get back when the contract expires or is closed out. Usually the margin is put up with bonds to minimize financial cost. For Arabica the margin usually makes up about 10% of the value of the underlying for the entire contract. This makes the futures market highly leveraged as you get return on 100% of the contract value.

At the end of every day there is a mark to market, where the margin account is balanced for the days gain or loss. If the amount in the margin account is too low, the holder of the futures contract will receive a margin call to supplement the margin account. If the margin call is not met the clearing house will close out the position.

If we disregard the transaction costs, trading futures is a zero sum game where the gain of having one position is mirrored by a symmetric loss for the opposite position. Hence the expected return from the futures market should be zero minus any transaction costs. However, the party that experiences a loss will not necessarily regret its decision as the position was entered to hedge away price risk, while the other party accepted the initial risk for potential gain.

Even though the futures market is a zero sum game, and the market participants are not able to outsmart the market or earn from expected spot price movements, they may receive a compensation for taking on risk, known as risk premium. If the futures price is below the expected future spot price (backwardation), the buyer of the futures contracts will on average earn risk premium. If on the other hand the futures price today is higher than expected spot price at maturity (contango), the seller of the futures contract will on average have positive return. The futures contracts does not have to be held until expiration to earn the risk premium. As the maturity date of the contract draws nearer the futures price will converge on the spot price of the commodity. If there is to be no arbitrage opportunities the futures price and spot price will be equal at the time of maturity.

6.1 What determines the futures price?

But how is the futures prices determined? The following explanation is in line with Black (1976). The spot price that will prevail when the futures contract settles is unknown today. As the futures contracts are a means to lock in future prices, the market actors compare the current futures price to what they expect the future spot price will be at the futures contract maturity. This way the expected future spot price will be embedded in the futures price. If the spot price is expected to increase in the future this will be reflected in higher futures prices compared to today's spot price. If the spot price is expected to decrease, the opposite will be true.

When we look at the futures contracts with increasing maturities or the shape of the futures curve, you can see that the price become higher or lower as the maturities grow longer. This is referred to as the term structure. The futures curve, or the futures contracts with increasing time to maturity, is mainly either in backwardation or contango. Backwardation means that the further away the maturity is, the lower the futures price is compared to the expected price at maturity. Contango is the opposite, where futures contracts with long time to maturity has a higher price compared to the expected price than does contracts with a shorter time to maturity. As there are many different opinions as to what the expected spot price at maturity is and therefore no way of measuring it reliably it is customary to use the current futures price and say that it is the most exact estimate of the expected spot price at maturity that we have. Therefore the futures price is used to decide whether the futures market is in contango or backwardation. A measure of this is the difference between the futures price and the current spot price, called the basis, and it is defined as follows:

$$Basis_{t,T} = Spot\ price_t - F^T(t) \tag{1}$$

where $F^T(t)$ is the futures price for maturity *T* at time *t*. If basis is positive we say that the market is backwardated and if it is negative we say it is in contango.

But which factors influence the term structure and determines the futures price? When it comes to explaining the variation in futures prices there are two main theories. But they are not mutually exclusive.

According to the theory of normal backwardation by Keynes (1930) and Hicks (1939), the producers of commodities would hedge their price risk by going short in the futures market. For the speculators to be willing to buy futures, and take on the risk of lower spot prices the futures would have to be sold at a discount relative to the expected spot price at maturity. The difference between the futures price and spot price at maturity is a compensation for the price risk taken on by the buyers, namely risk premium. According to the theory of normal backwardation the risk premium would normally accrue to the buyers of futures. The theory of normal backwardation has later been extended by several authors linking the risk premium to the hedging pressure, or the relative short side held by producers. Following the hypothesis that the hedging pressure determines the risk premium if there is a majority of short side hedgers this would lead to contango and the risk premium accruing to the holders of long positions. On the other hand if there is a majority of long side hedgers this would lead to contango and the risk premium falling to the holders of short positions. In a study which will be discussed at greater length later on Gorton and Rouwenhorst (2006) find a risk premium that is consistent with the theory of normal backwardation.

The other theory is the Theory of Storage worked out by Kaldor (1939), Working (1949), and Brennan (1958) who links the futures prices to storage and inventories, leading to contango being a normal term structure. More precisely when we look at futures prices and which factors that determine the futures price in addition to the spot price, we need to look at interest rate, cost of storage and convenience yield. The convenience yield is the benefit attached to owning the physical commodity minus the storage, and it accrues only to the holders of the physical commodity and declines with increasing inventories. It is the value of the opportunity to meet sudden surges in demand or fill momentary deficits in production. If we assume that the futures markets are arbitrage-free, according to Working the futures price at maturity *T* is equal to the spot price adjusted for interest rate, convenience yield and warehouse cost by the relationship:

$$F_{t,T} = S_t\left(1 + r_{t,T}\right)^T + w_{t,T} - c_{t,T} \tag{2}$$

Where $F_{t,T}$ is the futures price at time t with maturity T, S_t is the spot price at time t, r_t is the cost of money or interest rate, and w_t is the warehouse cost from time *t* up until the maturity at *T*, c_t is the convenience yield on the commodity, which is a negative cost. If this equality does not hold there is an arbitrage opportunity.

Backwardation is connected with high convenience yield, and contango with carrying costs outweighing the convenience yield. When the market is in contango the futures price is expected to fall towards the spot price when the time moves towards maturity. In this situation carrying cost outweighs the convenience yield and the basis reflects storage costs for inventory holders.

Several studies have followed rejecting and supporting the various theories. Hirshleifer (1990) merged the theories of normal backwardation and storage by linking backwardation to lower levels of hedging pressure and contango to higher levels of hedging pressure. On the other hand Gorton, Hayashi and Rouwenhorst (2012) found no evidence of hedging pressure predicting risk premiums. Dewally et al. (2013) provide evidence that traders who hold positions opposite in sign to probable hedgers earn greater profits than traders who hold positions that align with likely hedgers, additionally they found that profits on long positions varied inversely with inventories and in line with price volatility. Findings that they claim are consistent with modern hypotheses on risk premium, hedging pressure and theory of storage.

There are three sources of return in the commodity futures market, spot price change, the roll yield, and interest income. The margin is usually posted in T-bills and earns interest income, additionally since you only post a fraction of the value of the underlying as collateral the rest of the value can be placed in bonds to earn interest income.

The roll yield depends on whether the relevant market is in contango or backwardation. Generally there is a divergence between the returns on futures and spot on the same underlying asset. This divergence is called the "roll yield" or roll return, and it is measured as the difference in return between the futures contract and the underlying asset. It is a common misperception that the roll yield represents a realized gain or loss at the date when the contract is rolled forward, as you e.g. sell low and buy high. But the contracts are different instruments and cannot be compared directly. Roll yield is really accumulated over the entire lifespan of the trade as the futures price converge on the spot price as it grows nearer to expiration. An investor cannot earn the spot return directly. To be directly exposed to the changes in the spot price you would need to buy the physical commodity itself with all the costs that entails. Such as storage costs, transportation costs, financing costs and insurance costs.

When the market is backwardated the roll yield is positive for long positions, and negative in situations of contango. At maturity the futures price equals the spot price, if not there would be arbitrage opportunities.

The return from the spot price change is the difference between the spot price when you entered a position and when you exit it. For a long position this will be positive if the spot price increases and negative if it decreases. The opposite is true for the short position. However, in some situations the roll yield can be greater than the spot return.

7 The Coffee Futures Contract

In this chapter I present and comment on the dataset that has been used in this study. I provide stylized facts on the commodity futures for Arabica and look closer at the historical term structure. Additionally I comment on some of the great price spikes.

7.1 The Arabica futures contract

The data has been obtained from quandl.com, and consists of daily settlement prices, volume and open interest on the Coffee "C" contract which is traded at ICE.

The dataset spans the period from January 1990 to December 2013. The quoted prices are for a standardized quality with delivery in New York. KC is the commodities contract symbol, and the series of contracts are compiled into a continuous data series KC# with # ranging from 1 for the closest contract, 2 for the next closest contract and so on. The continuous series has been compiled by quandl.com and I have used two versions. For creating the descriptive statistics for the contracts I have used "first-of-month roll method" with a price adjustment called "calendar-weighted method". This means that the contract will be rolled on the first of every roll-month, and that there is a smoothed out transition from one contract to the next by rolling into the new contract over several days. For the trading strategies I have used roll on "open-interest-switch" and no price adjustment. The roll on open-interest-switch implies that there will be a roll from one position to the next when the open interest in the second position is greater than in the first position. This usually occurs one month before contract expiration. By trading the contract with highest open interest the traded contract is always the most liquid. The prices reported are in US cents per pound, whilst the entire Arabica contract is on 37,500 pounds. There are five contracts listed each year, March, May, July, September, and December.

When we look at the different term structures in Table 4, we can see that the market is mostly in contango. However, the second position contract is often more so than the rest of the contracts or in backwardation. If we use the concepts of storage cost we may explain this phenomena. When the second position contract or the KC2 is in backwardation this may reflect a positive convenience yield caused by a possible fear of coffee shortage. The second position in January tends to be more contangoed than the rest of the further contracts.

This is probably because of storage cost. In January KC2 equals the May contract, this is the last futures that reaches expiration before the new harvest arrives, causing the storage cost on the May coffee being higher than the July coffee.

Table 4: Basis in percent of the KC1 contract

Period	KC2	KC3	KC4	KC5	KC6
1990-1995	-2.41 %	-4.40 %	-6.62 %	-8.83 %	-10.92 %
1996-2001	0.42 %	0.14 %	-0.35 %	-1.05 %	-2.09 %
2002-2007	-3.38 %	-6.54 %	-9.31 %	-11.83 %	-14.27 %
2008-2013	-1.49 %	-3.03 %	-4.41 %	-5.66 %	-6.82 %

Note: Basis as percent of KC1 calculated as: ((KC1-KC#)/KC1)*100 . When the basis is negative there is contango and in backwardation when it is positive.

When you study the basis of the Arabica futures contract, shown in percent of KC1 in Table 4, we can see that the term structure have mainly been in contango. Second and third position (KC2 & KC3), had however an average positive basis in the years 1996-2001, while the rest of the positions included was in backwardation. The state of contango is according to the theory of storage caused by storage costs, while backwardation is caused by convenience yield. When we take this into consideration I interpret the situation where we have first backwardation for the first positions then contango for the later ones, as a short term fear of delivery deficits causing high convenience yield and backwardation. In the long run however this fear is not that prominent and the term structure is shaped by the storage costs causing contango.

Table 5: Stylized facts on first position Arabica futures (KC1)

	N	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**
1990-2013	287	1.37 %	36.33 %	0.446	1.439
2002-2013	144	7.53 %	31.45 %	0.244	0.453
1990-2001	143	-4.51 %	11.72 %	0.583	1.586

Note: The table reports statistics for the annualized monthly log returns in the settle price of the first position contract KC1. Calculated on the first-of-month roll and calendar weighted series.

In Table 5 we can see some stylized facts on the first position futures contract for Arabica (KC1) on a monthly basis. The mean annualized return for the period 1990 to 2013 was 1.37%, for the period 1990 to 2001 it was - 4.51%, and for the most recent period 2002 to 2013 it was 7.53%. The negative returns in the first period is probably mainly caused by Vietnams great increase in production. Additionally, after the collapse of the coffee cartel and the limitations on exports gone a drop in prices is expected. The volatility is also higher in the first period than in the latter with a standard deviation of 11.72% vs. 31.45%. When it comes to the skewness and kurtosis, the skewness is positive in both periods signifying that the distribution of monthly returns are skewed to the left. Both periods have leptokurtic distribution of returns, but the period from 1990 to 2001 more so than the later period. This tells us that the variance in the first period is to a larger extent the result of infrequent but extreme variations than in the second period, which makes sense as we earlier saw that the 90s experienced more peaks.

Figure 1 and Figure 2 below show the monthly log returns and squared returns of the period 1990-2013.

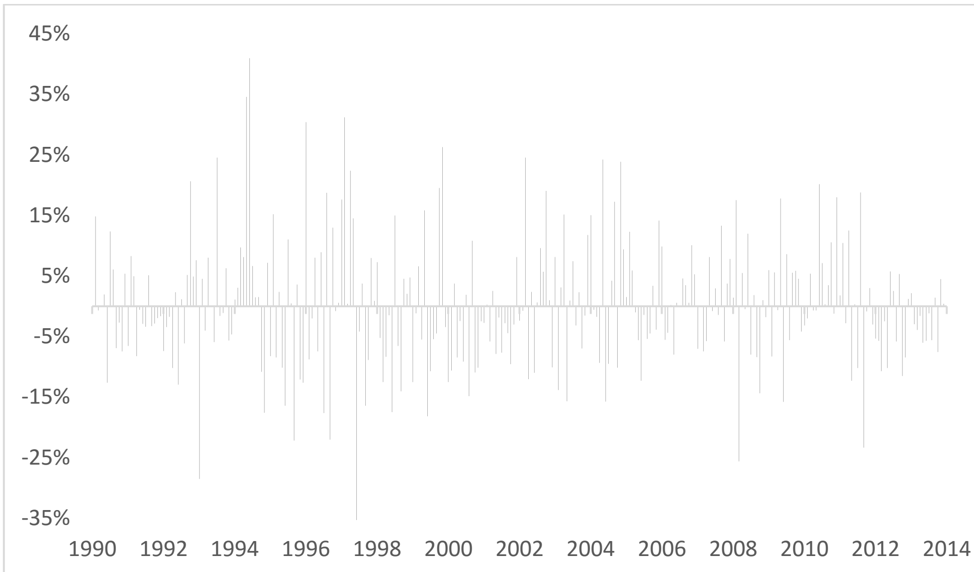

Figure 5: Monthly logarithmic return in KC1

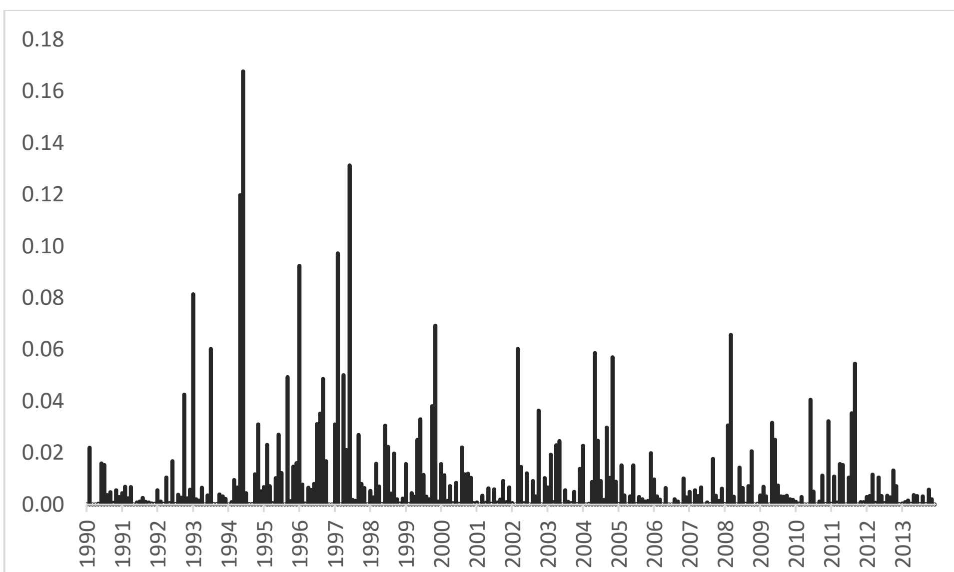

Figure 6: Squared monthly changes

There seems to be periods of higher volatility in the coffee prices. We can see a great spike in the settle price return in both 1994 and 1997. These were the last big frost years in Brazil. There is always a risk of frost in the winter months in Brazil, and when it happens it has a great impact on the markets. If we look at Figure 5 periods with great price increase seems to be followed by periods with great declines in price. This may be interpreted as overreactions to news of events that may cause smaller crops. One should also take into account that reporters of crop size and coming exports might benefit from higher coffee prices, and therefore underreport crop size and exaggerate negative events. According to Figure 6 there seemed to be bigger price swings in the 90s than the following decades, but this may merely be because of the instances of frost, and we may see similar spikes if we get new cases of frost.

8 Testing Out Technical Trading Strategies

In this section I will explain how the trades have been conducted, and how the returns from these trades have been calculated. Additionally I will go through how the results are reported, and the statistical tests the returns will be subjected to in order to determine if they are statistically greater than zero. To simplify the trading process I have made some assumptions. These make the trades deviate a little from reality, but I see the changes as relatively small. I will not buy contracts, but invest the entire portfolio each trade. All calculations are made on the settlement prices of each day. The settlement price is different from the close price. The settlement price is the average price over a certain period of trading, generally just before the market closes. I assume that it is possible to trade on the settlement price of the current day before the market closes, or that the settlement price is not very different from the opening price the following day. The margin requirements for the Arabica futures contract is supposed to cover any possible losses for one day. Therefore it varies depending on the volatility in the market, but is usually around 10% of the total contract value. Meaning that the contract is in reality leveraged 1:10. In this thesis I will assume the trades are fully collateralized. This would be achieved by investing an amount equal to the value of the entire contract in T-Bills every month.

8.1 Trading Strategies

I have created a set of systematic strategies that will send buy and sell signals when certain conditions or criteria are met. What these criteria's are will be explained closely under each strategy sub section. In addition to the buy and sell signals that leads to the entering of either long or short positions there is exit signals for when the positions should be exited. A roll signal for when the contract is rolled in to the next contract is an example of one exit signal.

Given that I post the margin in T-Bills and I have fully collateralized the contract in T-Bills I will add the return from T-Bills to the portfolio every month.

The transaction costs in the futures markets are lower than in the equities market. In the futures markets the transaction cost I have used is the one put forward by Locke and Venkatesh (1997). They found that the transaction cost is in the range of 0.0004% - 0.033% of notional value. The transaction cost that has been used in this thesis is a cautious 0.033%.

In this article I will assume zero Bid/Ask spread. I justify this by the fact that the closest Arabica futures contracts are highly liquid with a following low spread, and the cautious transaction cost I calculate. Additionally the actual futures contract are highly leveraged which would make the bid/ask spread very small.

Because of the special properties inherent in futures contracts we have to make some changes relative to trading equities, especially when we consider the roll. It is not enough to trade on buy and sell signals, we also have to exit the positions and possibly get into new positions when the roll or expiry of the futures contract is getting close. The roll will take place when there is a switch in open interest. Open interest is the total number of open futures contracts in the market, on the contract in question, at the end of each day. It is the amount of contracts that would see delivery if no contracts were closed out. As the contract is getting closer to settlement the open interest of the contracts will drop, as the futures is mainly used as a financial tool to speculate and manage risk rather than a way of trading physical coffee. Only a small fraction of the traded futures contracts will ever reach delivery. When the contract that is second closest to delivery becomes the contract with the highest open interest, the second position contract becomes in fact the first position contract in the trading strategy, and the third position becomes the second position. This way I will always trade the most liquid contracts, and reduce the risk of making or taking delivery. The open interest switch usually takes place a month before settlement of the contract.

8.1.1 Benchmark

To gain exposure to the commodities markets it is common to buy into an Exchange Traded Fund (ETF) or Exchange Traded Notes (ETN) that traces the price moves of a commodity or a set of commodities. For the coffee market, Barclays Bank iPath Pure Beta Coffee exchange traded note(ETN), CAFE for short, is an example of this. It is the issuing bank`s debt in the form of coffee futures which is rolled from contract to contract. These ETF`s or ETN`s are mainly long only, which means that if the market they are connected to is in contango they will lose on the roll yield. There are no such funds that cover the whole period of my data sample, CAFE was initiated in 2011. Therefore I have constructed my own "coffee ETN" for my sample period, which is long only, to mimic the alternatives for coffee exposure. The results from this long-only strategy is displayed in Table 6 below.

Table 6: Long-only strategy descriptive statistics

Period	Mean Return	Standard deviation	Sharpe ratio	T-stat vs. T-Bills	Percent Profitable
1990-2013	-2.55 %	18.35 %	-0.31	-1.51	37.19 %
2002-2013	-1.65 %	7.10 %	-0.44	-1.53	37.70 %
1990-2001	-3.45 %	24.95 %	-0.33	-1.14	36.67 %

Note: The return and standard deviation is annualized averages, and the t-statistic is against T-Bills.

As can be seen from Table 6 the long-only strategy has delivered a negative return in all periods, and a percent profitable of 36-38 percent. This is due to the coffee markets being mainly in contango.

8.1.2 Return calculation

The returns of each trade calculated as the simple return which is then calculated into the portfolio, which starts at 100, minus the transaction cost. The percent change in contract price from entering p_{t-1}, until exit p_t is the return. For long positions a positive change leads to positive return LR, and for short positions, negative change leads to positive return SR. For calculation of annualized mean return and standard deviations and so forth, the logarithmic change in the portfolio will be used. The returns that are reported is adjusted for both transaction cost and inflation. The portfolios are deflated by the Consumer Price Index (CPI) collected from the U.S. Department of Labor Bureau of Labor Statistic.[4]

The performance of the strategies are measured by the Sharpe Ratio from Sharpe (1966) , with the strategy`s mean return $\bar{r}_s$, minus risk free return $\bar{r}_f$, divided by the standard deviation of the strategy`s return σ_s.

[4] http://www.bls.gov/cpi/#data

The trading strategies that I have constructed is not always in position, there may be prolonged periods of time that the strategies hold no positions. It may therefore not be correct to judge them by their annualized return. Their performance will therefore also be measured in the two following ways:

Percent Profitable

$$percent\ profitable = winning\ trades/total\ nr.of\ trades \tag{3}$$

Profit factor

$$Profit\ Factor = Gross\ Profit/Gross\ Loss \tag{4}$$

8.2 Statistical Tests of Performance

To ascertain if the returns I get from the implemented trade strategies are statistically larger than risk free or benchmark return I will use a t-test, because the strategies does not have matching holding periods or number of trades with what I am comparing it with I use the unpaired t-test. The unpaired t-test compares the means of two series, and checks if they are significantly different. Risk free return or zero profit, is the 3-month T-bill return, benchmark return is a long only strategy. To check if the return generated from the various trading strategies is significantly greater than zero, or the benchmark I will apply a one-sided or one-tailed t-test. In the tables the t-value will be reported under the returns for each strategy. As this is a one-sided test it is not the absolute value of the t-statistic, but the actual value that is crucial. These strategies are as earlier mentioned based on effects caused by cognitive biases described in behavioral finance, therefore the strategies will be tested on the entire period from January 1990 to December 2013.

To test the robustness of the strategies, I have tested the performance in two sub periods. This is done to check if the strategies work systematically or if they just seem to work due to random conditions in the observation period.

8.3 Technical Trading Rules

The following trading rules are based on technical analysis which has been discussed earlier. To simplify the calculation of the buy/sell signals we have used continuous series with a built in roll. Optimally as there is a roll the next position should be the basis for signal calculation, but because we use continuous series this has not been done. The rolls have been executed, but the signal calculations will be performed on the continuous series. This will cause a slight deviation from reality, but because of the high correlation between the series the deviation should not be that great. In addition there are financial instruments like ETF`s and CDF`s that enables trade on the continuous contract without having to consider the roll.

8.3.1 Support and Resistance

This is a contrarian trading strategy which is made to exploit possible reversion in prices. If there is overreaction to news or herding in the market, the price will revert back, to correctly reflect the fundamentals. To determine whether the contract is over- or underpriced I have used Support and Resistance based on pivot points. This method creates three levels, resistance, pivot point and support. Resistance is the highest level which theoretically works as a price ceiling which the price bounces back down from. Support is lowest level which is supposed to act as a floor which the price should bounce back up from. In the middle we have the pivot point, which is a type of moving average. As most of the trading rules in technical analysis this is a subjective rule, which I have calculated in the following manner: Pivot point is the sum of the highest price, the lowest price and the average price over the X last days, divided by 3. The Support is calculated as two times the pivot point minus the highest price the X last days, and the Resistance as two times the pivot point minus the lowest price over the X last days. I have tested the strategy with four different time intervals, 5, 20, 50 and 100 days. Shorter intervals lead to more sensitive strategies that generate more signals than the longer intervals.

In addition to the support and resistance, the pivot point also works as resistance when the price is below it, and as support when the price is above. The strategy also takes the possibility of break-outs into account. This is what happens when the price breaks through the support going down or resistance going up. A break-out is interpreted as a new trend and generates a buy signal.

The buy and sell signals are generated when one of the following occurs:

Enter long position when one of the following occurs: The price is under pivot, support or resistance for one day, then over for two consecutive days. Regarding the resistance or pivot this is interpreted as broken resistance and a break out. Or for the support and pivot it is interpreted as the support holding and reversion of price trajectory. A long position is exited when there is a either a short signal or a roll signal. Figure 7 below illustrates the long signals in relation to the support, resistance and pivot point lines. In reality these lines fluctuate with the price, but I have made them straight in the illustration to make them more clear.

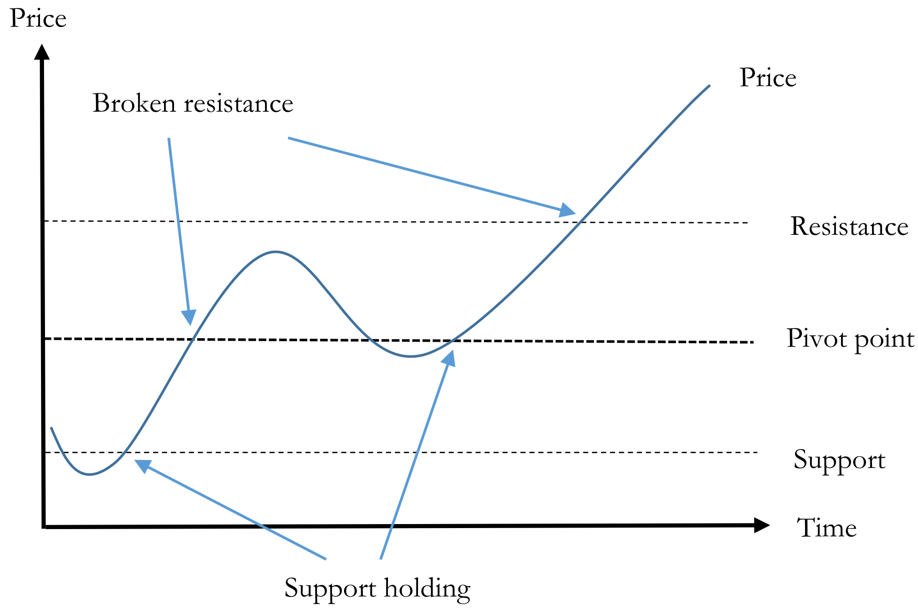

Figure 7: Illustration of long signals for support and resistance

Enter short position when one of the following occurs: The price is over the markers for one day, then under for two consecutive days. The interpretation is then that the support is tested for pivot and support, and as the resistance holding for pivot and resistance. A short position is exited when there is a either a long signal or a roll signal. Figure 8 shows when the short signals occur.

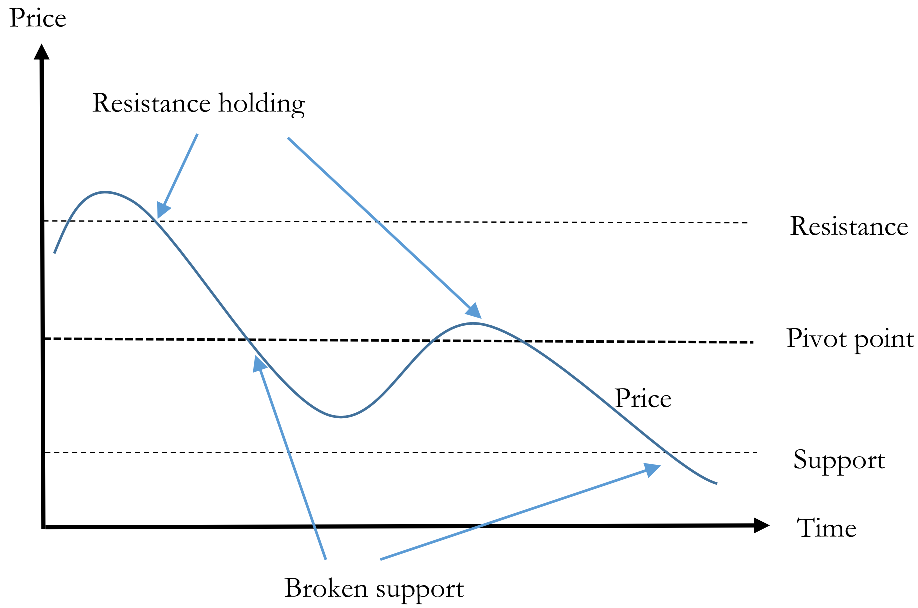

Figure 8: Illustration of short signals for support and resistance

In Table 7 we can see the average annualized return and standard deviation of the strategy, with the Sharpe ratio based on T-Bills as well as skewness and kurtosis. In Table 8 the amount of short and long trades are reported with the average return from each position. Additionally you can see the profit factor, and the percent profitable.

Table 7: Test results for Pivot Point based Support and Resistance

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	S&R(5)	-5.74 %	13.91 %	-0.638	-0.537	7.794
	t vs. Long only	(0.08)				
	t vs. T-Bills	(-3.16)				
	S&R(20)	-4.30 %	19.79 %	-0.376	-0.980	10.865
	t vs. Long only	(0.25)				
	t vs. T-Bills	(-0,02)				
	S&R(50)	3.72 %	21.40 %	0.028	0.262	2.654
	t vs. Long only	(1.20)				
	t vs. T-Bills	(0.13)				
	S&R(100)	1.10 %	18.49 %	-0.110	0.865	12.733
	t vs. Long only	(0.93)				
	t vs. T-Bills	(-0.53)				
2002-2013						
	S&R(5)	-1.02 %	2.27 %	-1.110	-0.756	3.941
	t vs. Long only	(0.25)				
	t vs. T-Bills	(-3.76)				
	S&R(20)	-1.79 %	9.13 %	-0.360	-0.024	3.197
	t vs. Long only	(0.16)				
	t vs. T-Bills	(-1.25)				
	S&R(50)	1.99 %	16.12 %	0.031	0.095	0.268
	t vs. Long only	(0.53)				
	t vs. T-Bills	(0.11)				
	S&R(100)	-2.53 %	7.11 %	-0.566	-0.502	2.368
	t vs. Long only	(0.08)				
	t vs. T-Bills	(-1.97)				
1990-2001						
	S&R(5)	-10.25 %	19.44 %	-0.774	-0.178	2.626
	t vs. Long only	(-0.08)				
	t vs. T-Bills	(-2.76)				
	S&R(20)	-6.75 %	26.44 %	-0.437	-0.750	5.636
	t vs. Long only	(0.20)				
	t vs. T-Bills	(-1.53)				
	S&R(50)	5.48 %	25.61 %	0.027	0.250	2.039
	t vs. Long only	(1.09)				
	t vs. T-Bills	(0.09)				
	S&R(100)	0.39 %	25.13 %	0.002	0.588	6.204
	t vs. Long only	(1.05)				
	t vs. T-Bills	(0.01)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 100 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if t > 1,65 at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Table 8: Overview of trades made with Support and Resistance.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	S&R(5)	590	585	-0.59 %	0.33 %	0.62	45.87 %
	S&R(20)	336	325	-0.54 %	0.55 %	0.77	44.93 %
	S&R(50)	217	208	0.14 %	0.04 %	1.11	45.41 %
	S&R(100)	172	164	-0.32 %	0.64 %	0.95	38.99 %
2002-2013							
	S&R(5)	288	290	-0.33 %	0.07 %	0.77	45.85 %
	S&R(20)	175	171	-0.34 %	0.30 %	0.88	44.51 %
	S&R(50)	111	105	0.13 %	0.02 %	1.11	45.37 %
	S&R(100)	97	99	-0.17 %	0.62 %	0.77	38.78 %
1990-2001							
	S&R(5)	302	295	-0.27 %	0.26 %	0.61	45.90 %
	S&R(20)	161	154	-0.20 %	0.24 %	0.73	45.40 %
	S&R(50)	106	103	0.01 %	0.02 %	1.11	45.45 %
	S&R(100)	75	65	-0.15 %	0.02 %	1.01	39.29 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

As can be seen from Table 7 and Table 8 we cannot reject that the strategies returns are similar or less than the long-only strategy. 50 days is the only strategy interval that delivers positive return in both sub periods. From Table 8 we can see that three of the four strategies have percent profitable of between 44-46 percent. And the 100 days intervals has only 38,99% percent profitable. This holds true for all periods, meaning that none of the strategies has a higher hit-rate than 50 %. But it is also clear that the mean return from the short trades are all positive, and only S&R(50) manages to earn a mean positive return on the long trades. The coffee market has mostly been in contango which probably results in the positive returns on the short trades.

8.3.2 Momentum and Relative Strength Index

The Relative Strength Index (RSI) is calculated as the sum of changes on days with positive changes the last N days multiplied by 100 divided by the sum of changes on days with positive change and the sum of changes with negative change for the last N days. I have calculated RSI with intervals of 5, 10, 15, and 20 trading days. To apply the RSI as a momentum indicator I have divided into groups for when I consider the contract as overbought or oversold. When the RSI enters the zone for overbought(70+) it signals an upward momentum and will therefore send a sell signal. When it falls below 70 again it signals a change in trend which sends an exit signal. A sell signal will be triggered if the RSI falls below 30, and the exit of the short position when the RSI rises above 30 again.

Buy/sell signals:

$$\begin{aligned} RSI > 70 &\rightarrow Buy \\ RSI < 70 &\rightarrow Exit \end{aligned} \tag{5}$$

$$\begin{aligned} RSI < 30 &\rightarrow Sell \\ RSI > 30 &\rightarrow Exit \end{aligned} \tag{6}$$

The results from these strategies are displayed in the tables below. The name of the rules refers to the amount of days used in calculating the RSI, RSI(5) is for instance the RSI calculated on the price changes of five days and so on.

Table 9: Test results for momentum strategies based on RSI

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	RSI(5)	-1.68 %	20.61 %	-0.234	-1.805	35.843
	t vs. Long only	(0.57)				
	t vs. T-Bills	(-1.14)				
	RSI(10)	1.54 %	14.13 %	-0.113	1.536	10.550
	t vs. Long only	(1.03)				
	t vs. T-Bills	(-0,01)				
	RSI(15)	3.05 %	13.25 %	-0.006	2.650	20.188
	t vs. Long only	(1.23)				
	t vs. T-Bills	(-0.03)				
	RSI(20)	2.09 %	12.70 %	-0.082	3.902	40.345
	t vs. Long only	(1.11)				
	t vs. T-Bills	(-0.39)				
2002-2013						
	RSI(5)	-2.86 %	6.86 %	-0.633	-0.222	0.909
	t vs. Long only	(0.04)				
	t vs. T-Bills	(-2.20)				
	RSI(10)	-3.47 %	6.31 %	-0.786	-0.454	2.399
	t vs. Long only	(-0.03)				
	t vs. T-Bills	(-2.74)				
	RSI(15)	-1.99 %	7.73 %	-0.450	-0.188	2.633
	t vs. Long only	(0.14)				
	t vs. T-Bills	(-1.56)				
	RSI(20)	-1.44 %	6.57 %	-0.447	-1.010	5.073
	t vs. Long only	(0.20)				
	t vs. T-Bills	(-1.54)				
1990-2001						
	RSI(5)	-0.49 %	28.33 %	-0.187	-1.430	19.179
	t vs. Long only	(0.65)				
	t vs. T-Bills	(-0.63)				
	RSI(10)	6.79 %	18.84 %	0.105	1.110	5.199
	t vs. Long only	(1.27)				
	t vs. T-Bills	(0.35)				
	RSI(15)	8.33 %	16.95 %	0.208	2.360	13.464
	t vs. Long only	(1.41)				
	t vs. T-Bills	(0.68)				
	RSI(20)	0.47 %	16.65 %	0.056	3.387	25.727
	t vs. Long only	(1.22)				
	t vs. T-Bills	(0.19)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 20 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if $t > 1{,}65$ at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Table 10: Overview of trades conducted with the RSI strategies.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	RSI(5)	326	347	-0.50 %	0.60 %	0.88	52.30 %
	RSI(10)	173	208	-0.38 %	0.61 %	0.99	51.71 %
	RSI(15)	106	144	-0.05 %	0.02 %	1.11	46.40 %
	RSI(20)	77	102	-0.50 %	1.09 %	1.11	58.10 %
2002-2013							
	RSI(5)	170	162	-0.19 %	0.36 %	0.75	49.70 %
	RSI(10)	89	98	0.18 %	0.38 %	0.64	45.99 %
	RSI(15)	59	64	0.24 %	0.01 %	0.80	43.09 %
	RSI(20)	45	44	0.21 %	0.66 %	0.82	57.30 %
1990-2001							
	RSI(5)	156	185	-0.31 %	0.24 %	0.93	54.84 %
	RSI(10)	84	110	-0.56 %	0.23 %	1.18	57.22 %
	RSI(15)	47	80	-0.29 %	0.00 %	1.47	49.61 %
	RSI(20)	32	58	-0.73 %	0.44 %	1.41	58.89 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

None of the RSI based momentum strategies are able to create a returns that is statistically significant greater than T-Bills or long-only. We can also see that the signals have a hit rate ranging from 43 to 58 percent. Not that different to what you would expect if the trades were conducted randomly. Again we can see that the long position predominantly have a negative mean return per trade, while the short trades are positive.

8.3.3 Trend Following Strategy

By applying simple and exponential moving averages to the price I hope to reveal a trend. If a possible trend is recognized buy or sell signals are generated that is constructed to go long in rising trends and go short downward trends. I have created five strategies that attempts this, the first is just a five day exponential moving average (EMA) that is compared to the current price. The EMA is more sensitive to price changes than the simple moving average as the closer prices are more heavily weighted. This is done in the following fashion:

$$EMA = Price_t * k + EMA_{t-1} * (1 - k) \tag{7}$$

where $Price_t$ is the price today, k=(2/(N+1), where N is the number of days in the moving average, and EMA_{t-1} is the EMA yesterday.

When the EMA crosses over the price there is a signal. If the EMA crosses through the price from below this is interpreted as an uptrend and sends a buy signal, if the price is crossed from above this is interpreted as a down trend and sends a sell signal. To decrease the amount of false signals I have put up a buffer on each side of the price that the EMA has to pass through to send a signal. It is the price minus 0.5% to send a sell signal and the price plus 4% to send a buy signal. As the market is mostly in contango I wanted the buy buffer to be greater.

The other strategies are composed of one simple moving average (SMA) and one EMA. Here the signals are generated when the EMA crosses the SMA. The same buffers apply to the SMA as to the price in the previous strategy.

As discussed earlier there is no definite answer to how long a moving average (MA) should be. If it is too long many signals will be lost, and the signals may come too late to earn profit. If the MA is too short there may be many false signals. You can also use one or two MAs. Considering this I have tested a variety of MAs. To avoid too many false signals I have also added a buffer to the moving averages. As coffee is a storable agricultural commodity I expected it to be in contango due to storage costs, I therefore put in a larger buffer for the long signals than the short signals. The long buffer is 4% while the short buffer is -0.5%. Where I have used one MA I interpret the situation where the price moves above the MA plus 4% as a buy signal, and when it moves below minus 0.5% as a sell signal. In the strategies with one long and one short MA, when the short MA rises above the long MA is interpreted as a buy signal, and when the short MA falls below the long MA as a sell signal.

I stay in the position until the EMA comes back into the buffer zone, at which point I exit the position. There will also be an exit signal when there is a switch in open interest (the open interest in the second position becomes higher than in the first position) and there is a roll. Below follows the results from this trading strategy. The rule name reflects the amount of days used in the moving averages, the first number is the EMA and the second is the SMA, which means that 5vs10 stands for one 5 day EMA and one 10 day SMA. 5vs0 is a five day EMA against the futures price.

Table 11: Test results for trend following strategies based on moving averages

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	5vs0	17.96 %	22.70 %	0.653	-0.443	3.109
	t vs. Long only	(2.68)				
	t vs. T-Bills	(2.92)				
	5vs5	12.80 %	15.61 %	0.619	0.063	0.827
	t vs. Long only	(2.35)				
	t vs. T-Bills	(2.83)				
	5vs10	7.92 %	19.24 %	0.248	-0.383	8.926
	t vs. Long only	(1.71)				
	t vs. T-Bills	(1.16)				
	10vs20	7.34 %	16.07 %	0.261	-0.229	3.800
	t vs. Long only	(1.71)				
	t vs. T-Bills	(1.22)				
2002-2013						
	5vs0	25.06 %	20.24 %	1.164	0.102	0.572
	t vs. Long only	(2.47)				
	t vs. T-Bills	(3.61)				
	5vs5	9.61 %	14.72 %	0.552	-0.022	1.214
	t vs. Long only	(1.29)				
	t vs. T-Bills	(1.82)				
	5vs10	-0.41 %	12.13 %	-0.157	-0.115	1.116
	t vs. Long only	(0.30)				
	t vs. T-Bills	(-0.54)				
	10vs20	5.49 %	12.93 %	0.309	0.470	0.993
	t vs. Long only	(0.91)				
	t vs. T-Bills	(1.04)				
1990-2001						
	5vs0	11.24 %	24.79 %	0.260	-0.670	3.844
	t vs. Long only	(1.49)				
	t vs. T-Bills	(0.84)				
	5vs5	16.07 %	16.40 %	0.687	0.095	0.545
	t vs. Long only	(1.97)				
	t vs. T-Bills	(2.17)				
	5vs10	16.87 %	24.14 %	0.500	-0.593	6.653
	t vs. Long only	(1.87)				
	t vs. T-Bills	(1.58)				
	10vs20	0.74 %	18.68 %	0.236	-0.492	3.690
	t vs. Long only	(1.45)				
	t vs. T-Bills	(0.77)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 20 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if t > 1,65 at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Table 12: Overview of trades conducted with the trend following strategies.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	5VS0	64	1168	0.01 %	0.11 %	1.78	51.54 %
	5VS5	8	540	0.01 %	0.07 %	1.63	52.74 %
	5VS10	51	391	0.00 %	0.06 %	1.18	47.74 %
	10VS20	9	357	0.01 %	0.05 %	1.44	53.28 %
2002-2013							
	5VS0	9	613	0.01 %	0.03 %	1.83	52.09 %
	5VS5	0	272	0.01 %	0.04 %	1.57	52.21 %
	5VS10	14	192	0.01 %	0.04 %	1.00	44.17 %
	10VS20	0	174	0.01 %	0.02 %	1.43	49.43 %
1990-2001							
	5VS0	55	555	0.00 %	0.08 %	1.25	50.98 %
	5VS5	8	268	0.00 %	0.04 %	1.93	53.26 %
	5VS10	37	199	-0.01 %	0.02 %	1.46	50.85 %
	10VS20	9	183	0.00 %	0.03 %	1.48	56.77 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

The trend following strategies based on moving averages do all yield a positive return for the entire period, and all but one variation in the sub periods. The returns of the strategies 5vs0 and 5vs5 are significantly greater than T-Bills and the long only benchmark at the 5% level for the entire period, but 5vs5 is the only strategy that delivers statistically greater results in both sub-periods. The p-value for the 5vs5 strategy is 0.24% against T-Bills and 0.98% against long-only, which means I can reject the null hypothesis at a 1 % level. However, when we look at the percent profitable, it is not much over 50% for the entire period or the sub periods. This might suggests that the return, even though significantly greater than what it is compared against, can be the results of lucky guesses. The larger buffer on the long side than the short side, may also have pushed this strategy in a direction of short only which profits on the roll return due to this market being mainly in contango. I may also argue that although these strategies do not have a high hit rate, they earn significantly positive returns. Meaning that even though the strategy often misses, the hits lead to greater profits that outweigh the losses. The profit factor of the 5vs5 strategy has a profit factor of 1.63 for the entire period, meaning that the profit outweigh the loss 1 to 1.63.

9 Concluding Remarks

In this study, I test out simple technical trading strategies in the futures market for Arabica coffee. The data covers the period from January 1990 to December 2013, with two sub periods, 1990-2001 and 2002-2013. I conclude that most of the strategies tested out do not able provide excess returns that are statistically greater than zero. The only strategy that generates returns that are statistically greater than that of T-Bills is the moving average trend following strategy 5vs5, which is a strategy built on two 5 day moving averages, one simple and one exponential that generates buy and sell signals when the EMA crosses the SMA, plus a buffer. However, it should be mentioned that by repeatedly testing trading strategies on the same data, you might get a false positive. The 5vs5 had a p-value of 0.98% against long-only, meaning that the t-test is saying that the likelihood of getting this extreme results by chance is only 0.98% percent, implying that about every 100 times you expect to get a false positive. Taking the fairly low rate of percent profitable and that the other trend following strategies did not yield statistically significant results I will not conclude that trend following strategies of the kind I have constructed are able to make positive returns in the coffee futures market.

Many of the strategies have obtained better results than the long only strategy, which has lost money through all periods. Even though beating it is no impressing feat, the alternative strategies may be better options if exposure to the coffee market is what you seek. It should be taken into account that the constructed strategies are more short than long. A fact that might remove the negative correlation with inflation. Additionally, the cost of administrating the strategies are probably higher than the long only, and this has not been taken into account as I do not know how much this difference would constitute.

Earlier studies have concluded that momentum strategies earn positive returns in the commodities markets. Assuming that their findings are correct I should expect that although not exactly similar, the trend following strategies yielded some of the same results. There are several reasons I can see that may explain why they do not. Firstly the other studies have tested several commodities at once, which makes it possible to act on only the strongest signals, it also provides a diversification effect. Secondly, most of the other studies have covered a longer period of time. It may be that the markets have become more efficient and that these opportunities for earning excess return have diminished or disappeared. The findings in my study suggest that most of the strategies I have constructed performed better in the 90`s than after 2001. There has undeniably been an explosion in computers processing power since 1990, which have made quantitative analysis of the markets easier and more readily available. Thirdly, the earlier studies have mostly applied fixed holding periods. If the lacking results from my study is caused by too early exits of the positions, the fixed holding periods would avoid this problem.

The subjective nature of technical analysis and the strategies constructed, may lead proponents of technical analysis to dismiss my findings as based on wrong understanding of the field. It is important to emphasize that I have only covered a small part of technical analysis, and the parts I have covered may be executed in many other ways. This paper can be seen as a small contribution to testing of trading rules based on technical analysis, and other aspects of technical analysis can be an object for further research.

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11 Appendices

Appendix 1: Long-only strategy descriptive statistics

Period	Mean Return	Standard deviation	Sharpe ratio	T-stat vs. T-Bills	Percent Profitable
1990-2013	-2.55 %	18.35 %	-0.31	-1.51	37.19 %
2002-2013	-1.65 %	7.10 %	-0.44	-1.53	37.70 %
1990-2001	-3.45 %	24.95 %	-0.33	-1.14	36.67 %

Note: The return and standard deviation is annualized averages, and the t-statistic is against T-Bills.

Appendix 2: The unpaired t-test

Unpaired test statistic:

$$T = \frac{\widehat{D}}{SE\widehat{D}} = \frac{\bar{X} - \bar{Y}}{S_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{8}$$

Interpolated variance

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} \tag{9}$$

Where $\bar{X}$ is the mean return from the strategy, and $\bar{Y}$ the mean return from the T-Bills or long-only strategy. $SE\widehat{D}$ is the standard error of the difference between the mean returns for the strategy and T-Bills or long-only. $\widehat{D}$ is the difference between the mean returns for the strategy and the T-Bills or long.only.

For a right sided test the critical t-value is 1.65. If the t-value is greater than 1.65 you can reject that the strategies return is equal or less than the T-Bills or long-only.

Appendix 3: Test results for Pivot Point based Support and Resistance

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	S&R(5)	-5.74 %	13.91 %	-0.638	-0.537	7.794
	t vs. Long only	(0.08)				
	t vs. T-Bills	(-3.16)				
	S&R(20)	-4.30 %	19.79 %	-0.376	-0.980	10.865
	t vs. Long only	(0.25)				
	t vs. T-Bills	(-0,02)				
	S&R(50)	3.72 %	21.40 %	0.028	0.262	2.654
	t vs. Long only	(1.20)				
	t vs. T-Bills	(0.13)				
	S&R(100)	1.10 %	18.49 %	-0.110	0.865	12.733
	t vs. Long only	(0.93)				
	t vs. T-Bills	(-0.53)				
2002-2013						
	S&R(5)	-1.02 %	2.27 %	-1.110	-0.756	3.941
	t vs. Long only	(0.25)				
	t vs. T-Bills	(-3.76)				
	S&R(20)	-1.79 %	9.13 %	-0.360	-0.024	3.197
	t vs. Long only	(0.16)				
	t vs. T-Bills	(-1.25)				
	S&R(50)	1.99 %	16.12 %	0.031	0.095	0.268
	t vs. Long only	(0.53)				
	t vs. T-Bills	(0.11)				
	S&R(100)	-2.53 %	7.11 %	-0.566	-0.502	2.368
	t vs. Long only	(0.08)				
	t vs. T-Bills	(-1.97)				
1990-2001						
	S&R(5)	-10.25 %	19.44 %	-0.774	-0.178	2.626
	t vs. Long only	(-0.08)				
	t vs. T-Bills	(-2.76)				
	S&R(20)	-6.75 %	26.44 %	-0.437	-0.750	5.636
	t vs. Long only	(0.20)				
	t vs. T-Bills	(-1.53)				
	S&R(50)	5.48 %	25.61 %	0.027	0.250	2.039
	t vs. Long only	(1.09)				
	t vs. T-Bills	(0.09)				
	S&R(100)	0.39 %	25.13 %	0.002	0.588	6.204
	t vs. Long only	(1.05)				
	t vs. T-Bills	(0.01)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 100 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if t > 1,65 at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Appendix 4: Overview of trades made with Support and Resistance.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	S&R(5)	590	585	-0.59 %	0.33 %	0.62	45.87 %
	S&R(20)	336	325	-0.54 %	0.55 %	0.77	44.93 %
	S&R(50)	217	208	0.14 %	0.04 %	1.11	45.41 %
	S&R(100)	172	164	-0.32 %	0.64 %	0.95	38.99 %
2002-2013							
	S&R(5)	288	290	-0.33 %	0.07 %	0.77	45.85 %
	S&R(20)	175	171	-0.34 %	0.30 %	0.88	44.51 %
	S&R(50)	111	105	0.13 %	0.02 %	1.11	45.37 %
	S&R(100)	97	99	-0.17 %	0.62 %	0.77	38.78 %
1990-2001							
	S&R(5)	302	295	-0.27 %	0.26 %	0.61	45.90 %
	S&R(20)	161	154	-0.20 %	0.24 %	0.73	45.40 %
	S&R(50)	106	103	0.01 %	0.02 %	1.11	45.45 %
	S&R(100)	75	65	-0.15 %	0.02 %	1.01	39.29 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

Appendix 5: Test results for momentum strategies based on RSI

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	RSI(5)	-1.68 %	20.61 %	-0.234	-1.805	35.843
	t vs. Long only	(0.57)				
	t vs. T-Bills	(-1.14)				
	RSI(10)	1.54 %	14.13 %	-0.113	1.536	10.550
	t vs. Long only	(1.03)				
	t vs. T-Bills	(-0,01)				
	RSI(15)	3.05 %	13.25 %	-0.006	2.650	20.188
	t vs. Long only	(1.23)				
	t vs. T-Bills	(-0.03)				
	RSI(20)	2.09 %	12.70 %	-0.082	3.902	40.345
	t vs. Long only	(1.11)				
	t vs. T-Bills	(-0.39)				
2002-2013						
	RSI(5)	-2.86 %	6.86 %	-0.633	-0.222	0.909
	t vs. Long only	(0.04)				
	t vs. T-Bills	(-2.20)				
	RSI(10)	-3.47 %	6.31 %	-0.786	-0.454	2.399
	t vs. Long only	(-0.03)				
	t vs. T-Bills	(-2.74)				
	RSI(15)	-1.99 %	7.73 %	-0.450	-0.188	2.633
	t vs. Long only	(0.14)				
	t vs. T-Bills	(-1.56)				
	RSI(20)	-1.44 %	6.57 %	-0.447	-1.010	5.073
	t vs. Long only	(0.20)				
	t vs. T-Bills	(-1.54)				
1990-2001						
	RSI(5)	-0.49 %	28.33 %	-0.187	-1.430	19.179
	t vs. Long only	(0.65)				
	t vs. T-Bills	(-0.63)				
	RSI(10)	6.79 %	18.84 %	0.105	1.110	5.199
	t vs. Long only	(1.27)				
	t vs. T-Bills	(0.35)				
	RSI(15)	8.33 %	16.95 %	0.208	2.360	13.464
	t vs. Long only	(1.41)				
	t vs. T-Bills	(0.68)				
	RSI(20)	0.47 %	16.65 %	0.056	3.387	25.727
	t vs. Long only	(1.22)				
	t vs. T-Bills	(0.19)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 20 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if t > 1,65 at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Appendix 6: Overview of trades conducted with the RSI strategies.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	RSI(5)	326	347	-0.50 %	0.60 %	0.88	52.30 %
	RSI(10)	173	208	-0.38 %	0.61 %	0.99	51.71 %
	RSI(15)	106	144	-0.05 %	0.02 %	1.11	46.40 %
	RSI(20)	77	102	-0.50 %	1.09 %	1.11	58.10 %
2002-2013							
	RSI(5)	170	162	-0.19 %	0.36 %	0.75	49.70 %
	RSI(10)	89	98	0.18 %	0.38 %	0.64	45.99 %
	RSI(15)	59	64	0.24 %	0.01 %	0.80	43.09 %
	RSI(20)	45	44	0.21 %	0.66 %	0.82	57.30 %
1990-2001							
	RSI(5)	156	185	-0.31 %	0.24 %	0.93	54.84 %
	RSI(10)	84	110	-0.56 %	0.23 %	1.18	57.22 %
	RSI(15)	47	80	-0.29 %	0.00 %	1.47	49.61 %
	RSI(20)	32	58	-0.73 %	0.44 %	1.41	58.89 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

Appendix 7: Test results for trend following strategies based on moving averages

Period	Rule	Return	Standard Deviation	Sharpe Ratio	Skewness	Kurtosis
1990-2013						
	5vs0	17.96 %	22.70 %	0.653	-0.443	3.109
	t vs. Long only	(2.68)				
	t vs. T-Bills	(2.92)				
	5vs5	12.80 %	15.61 %	0.619	0.063	0.827
	t vs. Long only	(2.35)				
	t vs. T-Bills	(2.83)				
	5vs10	7.92 %	19.24 %	0.248	-0.383	8.926
	t vs. Long only	(1.71)				
	t vs. T-Bills	(1.16)				
	10vs20	7.34 %	16.07 %	0.261	-0.229	3.800
	t vs. Long only	(1.71)				
	t vs. T-Bills	(1.22)				
2002-2013						
	5vs0	25.06 %	20.24 %	1.164	0.102	0.572
	t vs. Long only	(2.47)				
	t vs. T-Bills	(3.61)				
	5vs5	9.61 %	14.72 %	0.552	-0.022	1.214
	t vs. Long only	(1.29)				
	t vs. T-Bills	(1.82)				
	5vs10	-0.41 %	12.13 %	-0.157	-0.115	1.116
	t vs. Long only	(0.30)				
	t vs. T-Bills	(-0.54)				
	10vs20	5.49 %	12.93 %	0.309	0.470	0.993
	t vs. Long only	(0.91)				
	t vs. T-Bills	(1.04)				
1990-2001						
	5vs0	11.24 %	24.79 %	0.260	-0.670	3.844
	t vs. Long only	(1.49)				
	t vs. T-Bills	(0.84)				
	5vs5	16.07 %	16.40 %	0.687	0.095	0.545
	t vs. Long only	(1.97)				
	t vs. T-Bills	(2.17)				
	5vs10	16.87 %	24.14 %	0.500	-0.593	6.653
	t vs. Long only	(1.87)				
	t vs. T-Bills	(1.58)				
	10vs20	0.74 %	18.68 %	0.236	-0.492	3.690
	t vs. Long only	(1.45)				
	t vs. T-Bills	(0.77)				

Note: The annualized monthly return and standard deviation, with Sharpe ratio against risk-less return (3 month T-Bills), skewness and kurtosis for the strategies with intervals from 5 days up to 20 days. The numbers in parenthesis is the t-statistic when tested against the mean of T-Bills and Long-only. Since this is a right-sided one tail test the null hypothesis is rejected if t > 1,65 at a 5% significance level.
Where the null hypothesis is that the strategy mean return is less than or equal to the mean return of long only or T-Bills.

Appendix 8: Overview of trades conducted with the trend following strategies.

Period	Rule	N(Long)	N(Short)	Long Return	Short Return	Profit Factor	Percent Profitable
1990-2013							
	5VS0	64	1168	0.01 %	0.11 %	1.78	51.54 %
	5VS5	8	540	0.01 %	0.07 %	1.63	52.74 %
	5VS10	51	391	0.00 %	0.06 %	1.18	47.74 %
	10VS20	9	357	0.01 %	0.05 %	1.44	53.28 %
2002-2013							
	5VS0	9	613	0.01 %	0.03 %	1.83	52.09 %
	5VS5	0	272	0.01 %	0.04 %	1.57	52.21 %
	5VS10	14	192	0.01 %	0.04 %	1.00	44.17 %
	10VS20	0	174	0.01 %	0.02 %	1.43	49.43 %
1990-2001							
	5VS0	55	555	0.00 %	0.08 %	1.25	50.98 %
	5VS5	8	268	0.00 %	0.04 %	1.93	53.26 %
	5VS10	37	199	-0.01 %	0.02 %	1.46	50.85 %
	10VS20	9	183	0.00 %	0.03 %	1.48	56.77 %

Note: The amount of trades made in both short and long positions with the mean return per trade. Profit factor is the gross return divided by the gross loss. And percent profitable is the number of winning trades divided by the total amount of trades.

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