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Technical Trading and Commodity Price Fluctuations

Stephan Schulmeister

Research assistance: Eva Sokoll

September 2012

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AUSTRIAN INSTITUTE OF ECONOMIC RESEARCH

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Abstract

The study examines the empirical relevance of two antagonistic hypotheses of commodity price dynamics. The "fundamentalist hypothesis" implies that commodity prices are determined exclusively by supply and demand conditions in spot markets. The "bull-bear-hypothesis" assumes that also destabilising speculation plays an important role in the price formation process. The extent of commodity price fluctuations since the late 1980s, in particular the boom 2007-08 and the subsequent bust, can hardly be accounted for by market fundamentals. At the same time, trading volume on commodity derivatives exchanges has been quadrupling since mid-2000s. This increase was probably due to rising speculation, to a great extent based on technical trading systems. This presumption is confirmed by the results of testing the performance of 1,092 technical trading systems in the futures markets for crude oil, corn, wheat and rice. Most of the models would have been profitable not only over the entire sample period but also over most sub-periods. If one aggregates over the transactions and open positions of the 1,092 technical models, it turns out that technical commodity futures trading exerts an excessive demand (supply) pressure on commodity markets.

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0. Executive Summary

The study examines the empirical relevance of two antagonistic hypotheses for explaining the development of commodity prices (and of asset prices in general) since the late 1980s.

The "fundamentalist hypothesis" implies that commodity prices are determined exclusively by market fundamentals, i.e., by supply and demand conditions. Due to the predominance of rational market participants, speculation cannot distort commodities prices (and asset prices in general) systematically and/or persistently.

By contrast, the "bull-bear-hypothesis" holds that also destabilizing speculation plays an important role in the process of commodity price formation. By using trend-following trading techniques, speculators cause commodity prices to move in a sequence of long-term upward trends (bull markets) and downward trends (bear markets).

Four commodities are taken as basis for the empirical analysis, crude oil, corn, wheat and rice. The study covers the period from 1989 to mid-2011. The main results are as follows.

The extent of the oil price fluctuations, in particular the rise of oil prices from 20 $ in early 2002 to almost 150 $ in mid-2008, the subsequent fall to 35 $ and the following increase to roughly 120 $ in spring 2011, can hardly be accounted for by market fundamentals. This is especially true for the great oil price boom 2002/2007:

- Global oil inventories have risen substantially since 2002.
- The growth of global oil consumption has slowed down since 2005.
- Even though China's demand for oil was rising faster than global demand, it rose very continuously. Moreover, China produces roughly half of its oil consumption.
- The spectacular price boom over the first half of 2008 coincided with a continuous deterioration of the prospects for the global economy.

A comparison between supply and demand conditions in the spot markets for corn, wheat and rice on the one hand, and the development of the respective futures prices does also raise doubts about the relevance of the "fundamentalist hypothesis". Between 2000 und 2004, global inventories of these commodities strongly declined. Yet, over this period prices of corn, wheat and rice did not rise substantially. When the price boom took off around mid-2007 global production grew actually stronger than consumption (with the exception of rice).

Trading volume on commodity derivatives exchanges rose only moderately between 2000 and 2005, but has been quadrupling since then. The boom in trading activities was particularly strong between the 2nd quarter of 2007 and the 1st quarter of 2008. This increase was probably due to rising speculation, to great extent based on technical trading systems.

The main results of testing the performance of 1092 technical trading systems in the futures markets for crude oil, corn, wheat and rice are as follows:

- Over the entire sample period 1989/2011 the models produce an annual gross return of 10.8%, 3.7%, 1.8%, and 11.3% when trading oil, corn, wheat and rice futures, respectively.
- During the bull-bear-period of 2007 and 2008, the profitability of technical trading in commodity futures markets was exceptionally high.
- The profitability of technical commodity trading is exclusively due to the exploitation of persistent price trends. This is reflected by profitable positions lasting 2 to 5 times longer than unprofitable positions.

If one aggregates over the transactions and open positions of the 1092 technical models, it turns out that technical commodity futures trading exerts an excessive demand (supply) pressure on commodity markets. When technical models produce trading signals they are almost all either buying or selling, when they maintain open positions almost all of them are on the same side of the market, either long or short.

The results of the study on the interaction between technical trading systems and commodity price fluctuations as well as the developments summarized above suggest that the "bull-bear-hypothesis" is more in line with the empirical evidence of commodity price dynamics than the "fundamentalist hypothesis".

1. Motivation and objectives of the study

The extent of booms and busts in commodity markets has risen markedly since the mid-2000s. In particular, the spectacular rise of commodity prices between 2005 and the first half of 2008, their subsequent collapse and the new boom of commodity prices since mid-2010 call for a concrete explanation. Such an explanation would help to better understand the development of the global economy in recent years. This is so for at least four reasons:

- First, the bull market 2005/2008 increased production costs, deteriorated expectations and, hence, dampened economic growth between mid-2007 and mid 2008 (prior to the outbreak of the financial crisis).
- Second, rising commodity prices were the main cause of the acceleration of (headline) inflation which prevented central banks, notably the ECB, to loosen monetary policy in face of an economic slump.
- Third, the extent of the decline in commodities prices in the second half of 2008 dampened import demand of commodity producing countries and deepened the recession in advanced economies.
- Fourth, the new boom of commodity prices which took off in mid-2010 caused global inflation to rise again in spite of a slow-down in economic growth, in particular in Europe.

Notwithstanding the importance of the huge and widening fluctuations of commodities prices in recent years, there is no consensus among academic economists, practitioners and politicians about the causes of this development. However, one can classify the different (hypothetical) explanations into two distinct groups.

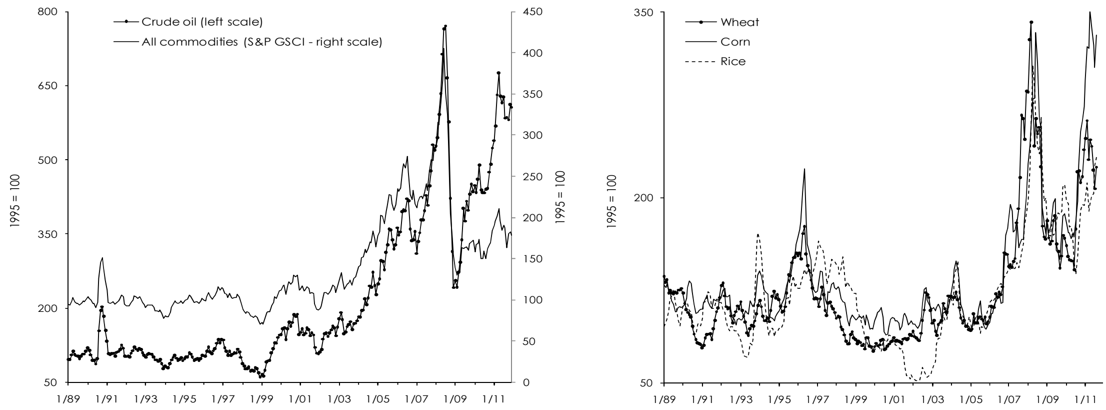
The first group holds that commodity prices are (almost) exclusively determined by market fundamentals. Due to the predominance of rational market participants, destabilizing speculation cannot distort commodities prices (and asset prices in general) in any systematic and/or persistent way. I call this proposition the "fundamentalist hypothesis" (in the literature usually called “efficient market hypothesis” or EMH).

The second group stresses the role of (destabilizing) speculation due to the “financialization” of commodity markets. In particular hedge funds, commodity index funds and investment banks have increasingly invested in commodity derivatives in recent years. The widely used trend-following trading techniques cause commodity prices to move in a sequence of long-term upward and downward trends, overshooting their fundamental equilibrium in both directions. From investigations into trading behaviour and price dynamics in different types of asset markets (in particular stock market and foreign exchange market) I derived a counter-hypothesis to the "fundamentalist hypothesis" or EMH (*Schulmeister – Schratzenstaller – Picek, 2008*). This alternative holds that overshooting is the most characteristic property of asset markets in general. Therefore I call this hypothesis the "bull-bear-hypothesis". It is one key objective of the present study to examine the relevance of this hypothesis for a better understanding of commodity price dynamics.

The most important demand and supply factors which (might) have driven up commodities prices in general and the oil price in particular are as follows (*IMF*, 2008; *Interagency Task Force*, 2008; EC, 2008; *Gilbert*, 2010B, *UNCTAD*, 2011):

- The strong expansion of overall demand for commodities due to high growth of the world economy in general and of emerging economies like China or India in particular.
- Specific factors stimulating the demand for particular commodities like the corn-based production of ethanol.
- Supply constraints in the oil market due to stagnating production of Non-OPEC-countries, due to the rising dependence on OPEC-oil and due to the decline in spare capacity.
- Reduced harvest yields in some countries in 2006 and 2007 (concerning in particular the supply of wheat).
- Geopolitical uncertainty concerning crude oil supply (Iraq, Iran, Nigeria, Venezuela).
- Low inventories of important commodities, especially of crude oil.

Figure 1: Commodity futures prices



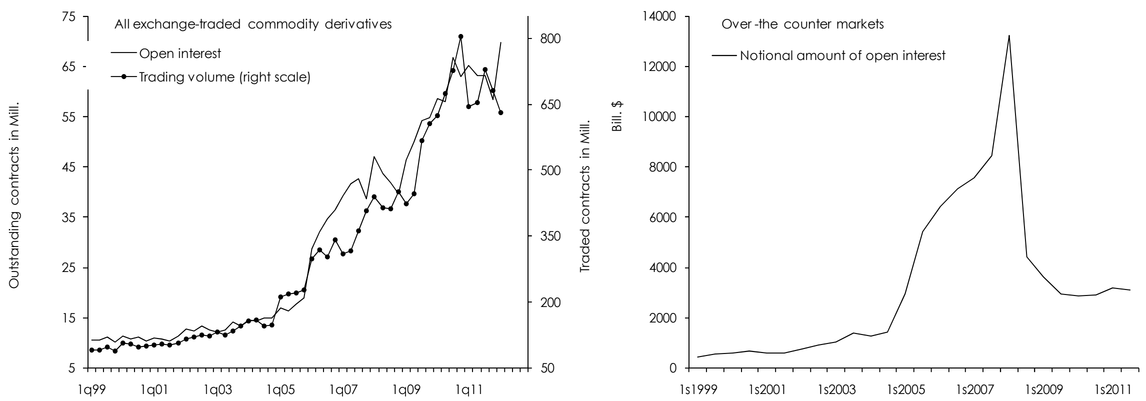
Source: NYMEX, S$P, CBOT.

Other fundamental factors which might have contributed to the commodity price increase include the marked dollar depreciation since 2002 as well as the loose monetary policy in the US and the related abnormally low level of dollar interest rates. The first factor provides an additional incentive for commodity suppliers to raise prices in order to (over)compensate the decline in their purchasing power due to the dollar depreciation. The second factor might have increased inflationary pressure in general due to an excessively rising money supply. In addition to that, declining interest rates provide an incentive for commodity producers to reduce current supply and postpone it to the future.

According to the "bull-bear-hypothesis", asset prices are not only driven by fundamentals but also by destabilizing speculation. This hypothesis is based on several observations and their interpretation (*Davidson*, 2008; *Podkolzina*, 2009; *UNCTAD*, 2009, 2011; *Gilbert*, 2010A, 2010B; *Gutierrez*, 2012; *Adammer – Bohl – Stephan*, 2012):

- Even though the fundamental factors mentioned above will have contributed to the fluctuations of commodity prices, they did not change that markedly since the mid-2000s as to explain the extent of booms and busts.
- In particular the acceleration of the commodity price boom between mid-2007 and mid-2008 can hardly be explained by market fundamentals as global economic growth was slowing down over this period.
- Similarly, the extent of the commodity price decline since mid-2008 cannot be accounted for by market fundamentals (until mid November commodity prices lost almost 60% of their peak values).
- The same is true for the new commodity bull market which took off around mid-2010. The weakness of the economic recovery in industrial countries after the great recession should have caused commodity prices to rise much slower than they actually did.
- Between 2005 and 2010, trading volume of commodity futures and options on exchanges has quadrupled, led by energy and agricultural instruments. It is hard to understand why the liquidity needed for an "orderly" price discovery process should have risen that strongly.
- Already in 2007, revenues of the 10 largest investment banks generated from commodity derivatives trading are estimated at 15 bill. $ (half of it is earned just by two banks, Goldman Sachs and Morgan Stanley – see www.bloomberg.com on June 16, 2008).

Figure 2: Commodity derivatives trading



Source: BIS.

These developments suggest that commodities markets have been increasingly shaped by bubble-like price movements in recent years. The upward trends of practically all important commodities were fed by increasingly "bullish" market sentiments. This "expectational bias" might have developed in the following steps:

- Prospects of tightening market conditions over the long run (e. g., oil shortage due to the "oil peak"), over the medium run (e. g., corn shortage due to bio-fuel production), as well as over the short run (e. g., wheat shortage due to bad harvests) cause market participants to expect rising prices of the respective commodities.
- Based on these fundamentals-oriented, "bullish" expectations, financial investors put additional funds into commodity derivatives which drive prices up in commodities futures markets. These price movements spill over to the spot markets since futures prices are used as benchmarks in contracts concerning the delivery of the physical commodities.
- Due to the "bullishness" in derivatives markets, short-term oriented speculators react much stronger to news in line with the expectation of rising prices than to news which contradict the "market mood". Hence, they put more money into long positions than into short positions and held long positions longer than short positions. As a consequence, upward commodity price runs last longer than downward runs causing commodities prices to rise in a stepwise process.
- Commodity price runs were lengthened by the use of trend-following trading systems of technical analysis. These systems try to exploit price runs by producing buy (sell) signals in the early stage of an upward (downward) run. The aggregate trading signals then feed back upon commodity prices.

The steep fall of all important commodities prices from their peaks reached around mid 2008 underpins the hypothesis that speculation in derivatives markets had caused prices to overshoot. The "fundamentalist hypothesis" can hardly explain why the price of crude oil, e. g., has declined by almost two thirds between early July 2008 and mid November 2008. This is so because the fundamental factors which purportedly have caused the oil price to rise have not changed so dramatically within such a short period of time.

The present study aims at documenting and evaluating the most important factors of commodity price dynamics according to the "fundamentalist hypothesis" as well as to the "bull-bear-hypothesis", in particular as regards the recent commodity price booms and busts. Four commodities are taken as basis for the empirical analysis, crude oil, corn, wheat and rice. The study covers the period from 1989 to mid-2011.[1]

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[1]) the present study is a follow-up study of *Schulmeister* (2009A) which covered the period until mid-2008. As regards methodology as well as the results concerning the period originally investigated, the present study draws heavily on *Schulmeister*, 2009.

The core part of the study focuses on the performance of 1092 popular technical trading systems in commodity futures markets as well as on the impact of the aggregate trading signals of these models on commodity price movements. This is so for two reasons. First, technical analysis is the most widely used trading technique in asset markets, and, second, the interaction between aggregate technical trading and commodity price dynamics has not yet been investigated.

More specifically, the main objectives of this report are as follows:

- Provide a survey of the recent literature about the price dynamics in commodity markets (chapter 2).
- Sketch the most important theoretical assumptions underlying the "fundamentalist hypothesis" and the "bull-bear-hypothesis" (chapter 3).
- Summarize the economists' debate over the oil price boom 2007/2008 (chapter 4).
- Discuss the relationship between commodity spot and futures prices (chapter 5).
- Sketch the development of daily futures prices of crude oil, corn, wheat and rough rice since 1989, in particular over the most recent booms and busts (chapter 6).
- Document the development of the most important indicators of supply and demand conditions in the spot markets of the four selected commodities (chapter 7).
- Summarize the development of trading activities in commodity derivatives markets (chapter 8).
- Discuss the general importance of technical trading in asset markets (chapter 9).
- Document the profitability of 1092 popular technical trading systems in the futures markets of crude oil, corn, wheat and rice (chapter 10).
- Analyze the impact of the aggregate trading signals of the 1092 technical models on the simultaneous as well as the subsequent commodity price movements (chapter 11).
- Compare the hypothetical position taking of the 1092 models to the actual position taking by different types of agents in US commodity futures markets (chapter 12).

2. Recent literature on trading behaviour and price dynamics in commodity markets

The recent literature on commodity price dynamics has been focusing on the boom which took off in the first half of the 2000s, cumulated in mid-2008 and collapsed afterwards. The main questions addressed by the studies are as follows:

- What are the main features of the "financialization" of commodity markets, i. e., the rising importance of longer-term investments of institutional investors like pension funds in commodity derivatives (in particular through index funds) as well as of short-term speculation by hedge funds and investment banks?

- Did the activities of financial investors and traders destabilize commodity prices and thereby strengthen the boom-bust-pattern observed since the mid-2000s? Or can these swings in commodity prices be explained by changes in supply and demand conditions in the spot markets?
- Are commodities a distinct asset class which attracts financial investors for reasons of diversification (optimizing the risk-return profile) or has the correlation between commodity prices and other asset prices increased?

The rising importance of financial investors in commodity markets is documented in several studies (*Domanski – Heath*, 2007; *CFTC*, 2008; *UNCTAD*, 2009; 2010; 2011; *Büyüksahin – Robe*, 2010; *Mayer*, 2009; *Irwin – Sanders*, 2010A, Gilbert, 2010B – see also the data bases of the Bank for International Settlements/BIS at www.bis.org and of the US Commodity Futures Trading Commission/CFTC at www.cftc.gov). The main tendencies can be summarized as follows:

- Trading volume and the number of outstanding contracts (open interest) in derivatives exchanges like Intercontinental Exchange (ICE), NYMEX (New York Mercantile Exchange) or Chicago Mercantile Exchange (CME) and Chicago Board of Trades (CBOT) quadrupled between 2005 and 2011. The expansion of trading activities was strongest over those sub-periods when also commodity prices increased the most (figures 1, 21 to 24).
- In the over the-counter (OTC) markets, the notional value of outstanding contracts increased to almost to 14 trillion $ until 2008 but fell sharply afterwards (figure 2). This indicates that trading activities have been shifted to the electronic platforms of exchanges.
- For most commodities, trading volume in derivatives markets has become several times higher than overall world production of the respective physical commodity (for crude oil see figure 20).
- Position taking by swap dealers - reflecting to a large extent the investments of their swap partners, in particular index funds, which track commodity price indices and therefore only hold long positions - and by money managers like hedge funds and investment banks which switch between long and short positions (mostly based on technical trading systems) have almost exploded since 2006 in US markets (figure 2).
- There is plenty of anecdotic evidence that the number of hedge funds engaged in commodity derivatives markets has risen dramatically over the past 10 years as did their capital invested in and their profits from commodity speculation (*Domanski – Heath*, 2007; Mayer, 2009; *UNCTAD*, 2011). The same is true for certain investment banks like

Goldman Sachs, JP Morgan or Deutsche Bank and for the leading commodity trading houses like Glencore, Cargill or Koch Industries (*Schneyer*, 2011).

Whereas there is a broad consensus in the literature that the activities of financial investors have expanded remarkably since the early 2000s, there are quite different answers to the question: Have these activities destabilized commodity price movements and thereby strengthened the boom which burst in 2008?

The majority of the studies conclude that this was most probably the case (*Davidson,* 2008*; Podkolzina,* 2009; *UNCTAD*, 2009; 2011; *Mayer*, 2009; *Gilbert*, 2010A, 2010B; *Gutierrez,* 2012*; Adammer – Bohl – Stephan,* 2012). Most studies document a statistical relationship - usually a Granger causality - between the change in the net positions of certain classes of traders (index traders, non-commercial traders, money managers) and futures price movements of the respective commodity.

Other studies using a similar methodology but different time periods, trader classes and/or data frequencies do not find a clear statistical relationship between position taking of certain types of investors and commodity price movements (e. g., *Irwin – Sanders*, 2010A, 2010B, *Blancard - Coulibaly,* 2012).

One important reason for the inconsistency of the results of these studies might lie in their methodology. More specifically, it seems to be in principle difficult to conclude from a statistical (non-)relationship between weekly (or even lower frequency) data about the net positions of certain types of market participants and (subsequent) price movements that destabilizing speculation is or is not at work. This is so for several reasons:

- The traditional assignment of hedging to commercial traders (those who deal with the physical commodity in the real economy) and speculation to non-commercials, in particular index traders and money managers, does not hold true. In modern markets, many – if not most – of the treasuries of the big players in the goods markets (in the case of crude oil, e. g., oil producers, trading houses, refiners) also speculate, and they use the same types of trading systems as hedge funds or investment banks.
- If the net position of a certain group or traders stays the same for one week to the other (the CFTC data from their "(Disaggregated) Commitment of Traders Reports" refer to position holdings on Tuesdays) it does not imply that these traders have not destabilized prices. If more traders want to go long (e. g. due to buy signals of trend-following models) than others want to go short, the price will rise until long and short positions are in equilibrium. This can also happen within a certain group of traders due to heterogeneous expectations and different trading models used. In effect, the price is driven up by technical trading (unrelated to fundamentals and, hence, destabilizing) but the net positions of the group remains the same. After all, the net position of all traders at any derivatives exchange is always zero, yet, prices fluctuate strongly (it is crucial for an

understanding of derivatives price dynamics to distinguish between "ex ante" and "ex post").

- Destabilizing speculation aims at exploiting the phenomenon of trending ("the trend is your friend"). Therefore, a stable relationship between position taking and (subsequent) price movements cannot prevail over time. In the early phase of an upward trend, a trend-following trading system opens a long position. Afterwards, the trading system "rides" the trend, e. g., it does not continue to buy whereas – hopefully – prices continue to rise (see chapter 8 for a more detailed discussion of this issue).
- There prevails an interaction between position taking and price movements in non-fundamental speculation. On the one hand, rising prices trigger buy signals, on the other hand, the execution of these signals feed-back on the upward trend. Therefore, evidence of destabilizing speculation does not call for a one-directional Granger causality running from position taking to price movements (as is often assumed, e. g., by *Mayer*, 2009).

Many studies analyse the increasingly parallel movement of different types of commodities prices. E. g., *UNCTAD* (2009) documents that the correlation between 13 commodities prices rose significantly between 1997 and 2008. The most important common factor linking the price development of different commodities is identified as investment strategies by financial agents who consider commodities as a new class of assets without taking into account the specific supply and demand conditions in the single commodities markets.

This hypothesis got support from the results of studies which document the increasing correlation between commodities prices and key financial asset prices like exchange rates and stock prices, not only based on daily data (*UNCTAD*, 2011) but also on high frequency data (*Bicchetti – Mastre*, 2012). Other studies by *Gilbert* (2010B) and *Büyüksahin – Robe* (2010) confirm that common factors related to financial activities have exerted a rising influence on commodity price dynamics in general (irrespective of the commodity-specific fundamentals).

The results of the research on the impact of the "financialization" of commodity markets on the dynamics of commodity prices, in particular with respect to the price hikes in 2008, served as incentive to undertake the present study. This is so because this study analyses profitability and price effects of the most popular speculation strategies, i. e., the use technical trading systems, in commodities markets, irrespective who is following these strategies. The extant studies, by contrast, have focused on the position taking of specific classes of traders, irrespective on which strategies the position taking is based upon.

3. The “fundamentalist hypothesis” and the “bull-bear-hypothesis” of asset price dynamics[2])

According to mainstream economic theory, asset prices are determined by the respective equilibrium conditions, i.e., by the so-called market fundamentals. Hence, destabilizing speculation will influence prices at best over the very short run (if at all). The main assumptions of the "fundamentalist hypothesis” can be summarized as follows (see also figure 1):

- The theoretical benchmark model of the “fundamentalist hypothesis” is an ideal, frictionless market where all participants are equipped with perfect knowledge and where no transaction costs exist ("world 0").
- The model underlying the "fundamentalist hypothesis” relaxes the assumptions of perfect knowledge and of no transaction costs. Also in this "world I" actors are fully rational, but they do not know the expectations of other actors. Hence, prices can reach a new equilibrium only through a gradual price discovery process (*Habermeier – Kirilenko,* 2003).
- The high transaction volumes in modern financial markets stem mainly from the activities of market makers. The latter provide just the liquidity necessary for facilitating and smoothing the movements of asset prices towards their fundamental equilibrium.
- Speculation is an indispensable component of both, the price discovery process as well as the distribution of risks. As part of the former, speculation is essentially stabilizing, i.e., it moves prices smoothly and quickly to their fundamental equilibrium (*Friedman*, 1953).
- An endogenous overshooting caused by excessive speculation does not exist. Any deviation of asset prices from their fundamental equilibrium is due to exogenous shocks and, hence, is only a temporary phenomenon.
- The emergence of news and shocks follows a random walk and so do asset prices. Therefore, speculation techniques based on past prices cannot be systematically profitable (otherwise the market would not even be "weakly efficient” – *Fama*, 1970).

The "bull-bear-hypothesis” perceives trading behaviour and price dynamics in asset markets as follows (“world II”):

- Imperfect knowledge is a general condition of social interaction. As a consequence, actors use different models and process different information sets.[3])
- Actors’ expectations and transactions are governed not only by rational calculations, but also by emotional und social factors.

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[2]) This chapter draws on *Schulmeister*, 2010.

[3]) In a recent, pathbreaking book, *Frydman - Goldberg* (2007) demonstrate that recognizing the importance of imperfect knowledge is key to understanding outcomes in financial markets.

- Not only are expectations heterogeneous but they are mostly formed only qualitatively, i.e., as regards the direction of an imminent price movement.
- Upward (downward) price movements – usually triggered by news - are lengthened by "cascades" of buy (sell) signals stemming from trend-following technical trading systems.
- The "trending" behaviour of asset prices is fostered by the dominance of either a "bullish" or a "bearish" bias in expectations. News which are in line with the prevailing "market mood" gets higher reaction than news which contradict the "market mood".
- In the aggregate, this behaviour of market participants causes price runs in line with the "market mood" to last longer than counter-movements. In such a way short-term runs accumulate to long-term trends, i.e., "bull markets" and "bear markets".
- The sequence of these trends then constitutes the pattern in long-term asset price dynamics: Prices develop in irregular cycles around the fundamental equilibrium without any tendency to converge towards this level.

To clarify the differences between the "fundamentalist hypothesis" and the "bull-bear-hypothesis", it is useful to distinguish between three (stylized) paths of asset prices (figure 1):

- In "world 0", new information at t = 1 causes the asset price to jump instantaneously from the old equilibrium at P = 100 (point A) to the new equilibrium at P = 104 (B). In t = 3, news cause the price to jump to P = 102 (at E), and in t = 5 the price jumps to P = 106 (at I).
- In "world I", it takes a series of transactions to move the price from P = 100 to P = 104 (from A to C). Since traders are rational, the movement will stop at the new fundamental equilibrium level and stays there until t = 3, when a new adjustment process takes off.
- In "world II", there exist traders who form their expectations according to the most recent price movements, i.e., when prices move persistently up (down) they expect the respective short-term trend to continue. Hence, they buy (sell) when prices are rising (falling), causing the price to overshoot (from C to K, from G to L, and from M to O).

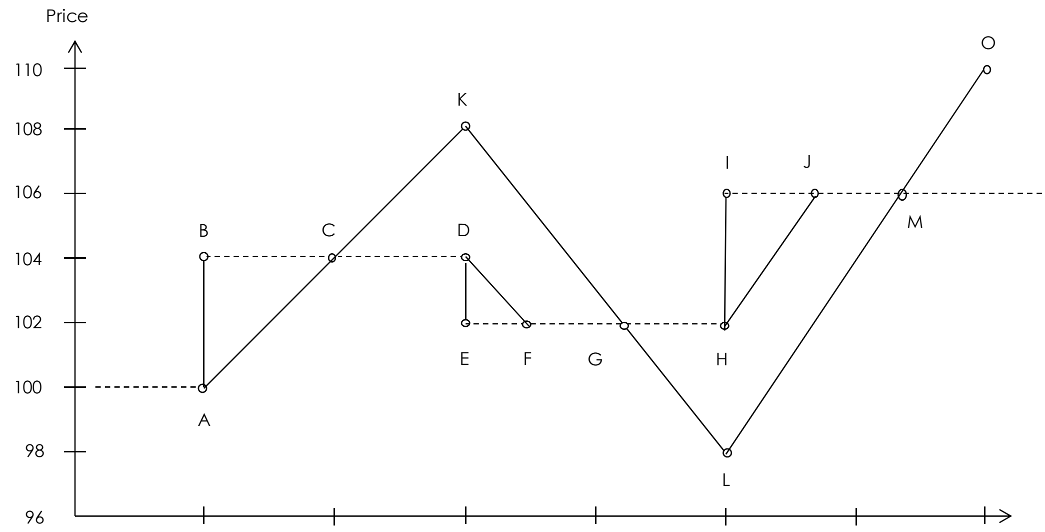
As a consequence of asset price "trending", rational investors (in the sense of profit-seeking) will try to systematically exploit this non-randomness in price dynamics. The conditions of "world II" will therefore almost inevitably emanate from those of "world I": If prices move smoothly from one fundamental equilibrium to the next, and if this price discovery process takes some time, then profit-seeking actors will develop trend-following trading strategies. The most popular types are summarized under the heading "technical analysis". [4])

Over more than 100 years people have developed and used a great variety of "technical" trading systems. All models of "technical analysis" have in common that they attempt to exploit price trends and by doing so they reinforce the pattern of asset price dynamics as a

[4]) For theoretical models dealing with the interaction of heterogeneous actors see *DeLong et al.*, 1990A and 1990B; *Frankel – Froot*, 1990; *De Grauwe – Grimaldi*, 2006; *Hommes*, 2006; *Frydman – Goldberg*, 2007.

sequence of upward and downward trends (for a comprehensive treatment of technical analysis see *Kaufman*, 1987; the interaction between technical trading and price dynamics is explored in *Schulmeister*, 2006, 2009B).

Figure 3: Three stylized paths of asset prices



In our stylized example those transactions (in "world II") which cause the price to overshoot (driving it from C to K, from G to L and from M to O) have to be considered "excessive" (as in "world I" price movements are triggered by news also in "world II"). These overshooting price changes amount to 12 between t = 1 and t = 7. The overall price changes over this period amount to 30 (8 + 10 + 12), whereas only cumulative price changes of 10 (4 + 2 + 4) would be fundamentally justified. This stylized example shows that once prices start to overshoot, their overall price path becomes much longer and the related transaction volumes get much bigger than under purely rational expectations (as in "world I"). Hence, the coincidence of a rising length of asset prices together with a rising discrepancy between transactions in (derivative) asset markets and in the (underlying) goods markets indicates a rising importance of trend-following speculation.

It is impossible to exactly prove one of the two hypotheses true and the other wrong. I shall therefore try to find empirical indicators which support rather the "fundamentalist hypothesis" or the "bull-bear-hypothesis". Based on the "stylistic" differentiation between "world I" and "world II" one could derive some support for the "bull-bear-hypothesis" from the following empirical observations (and vice versa for the "fundamentalist hypothesis" if these observations cannot be made):

- The discrepancy between the level of transactions in commodity derivatives markets and in the underlying spot market is extremely high (i.e., hedging is of little importance, most transaction are carried out between speculators with different expectations).

- This discrepancy rises strongly over the long run, in particular during phases of strong and persistent price movements.
- Technical trading systems are widely used in commodity futures markets and produce "abnormally" high profits over extended periods of time (i.e., several years).
- Long-term appreciations (depreciations) of commodity prices are brought about primarily by monotonic upward (downward) movements (i.e., price runs) lasting longer than counter-movements, and less by upward (downward) runs being steeper than counter-movements (the latter case would point at quick reactions of "fundamentalists" to news, the former case would reflect the persistence of price movements).

4. The debate over the oil price boom of the 2000s

I shall now briefly discuss the following questions: How should supply and demand conditions change in the markets of physical commodities if price movements are driven by destabilizing speculation rather than by fundamentals? Can the empirical evidence help to discriminate between the "fundamentalist hypothesis" and the "bull-bear-hypothesis"?

This issue has been intensively discussed in and across different Internet-blogs in the US. The probably most important initial Inputs were given by two prominent economists on their blogs, Paul Krugman (Princeton University and New York Times) and Jeffrey Frankel (Harvard University).[5]) The discussion has focused on the causes of rising crude oil prices, however, the arguments are equally valid for other exhaustible commodities which can easily be stored "underground", i.e., by reducing extraction (by contrast, the arguments do not apply to renewable commodities like food).

Initially, Krugman argued that if destabilizing speculation had actually driven up oil prices beyond their fundamental equilibrium then supply would exceed demand and this should show up in rising inventories. Such a strong accumulation of inventories as implied by an extreme, speculation-driven overshooting of oil prices is not observed. Krugman concluded therefore, that oil prices were not driven by destabilizing speculation. Others argued however, that due to the very low short-run demand and supply elasticities, the rise in inventories induced by overshooting oil prices might not show up in the data.

A (storable) commodity like crude oil represents not only the output of drilling and extraction and the input to other types of production (flow), but also a store of wealth (stock). Hence, one has to take into account the flow character as well as the stock character of commodities and also the role of price expectations. Mark Thoma (University of Oregon) built

[5]) See the respective contributions posted by Krugman on www.nytimes.com and by Frankel on http://content.ksg.harvard.edu/blog/jeff_frankels_weblog. Other Blogs which participated in the debate and provided interesting contributions are www.econbrowser.com, www.nakedcapitalism.com, and http://peakoildebunked.blogspot.com.

a simple model to analyze the interaction between supply of and demand for a commodity in the "flow market" as well as in the "(commodity) stock market" in relation to the current commodity price as well as to the expected future price (this stock-flow-model is described at Mark Thoma's Blog at http://economistsview.typepad.com). The model arrives at similar results as the traditional "flow model" used by Krugman: An increase in the expected future price of a commodity (e. g., triggered by the beliefs or irrational speculators) will have two effects, a temporary increase in the spot price, and a permanent increase in inventories of the commodity.

With respect to the possible effects of destabilizing commodity speculation, Mark Thoma concludes:

- "A signature of speculation of the type modelled here is changes in stocks. When the expected future price goes up, storage increases, when it goes down, storage decreases.
- An increase in the spot price over long periods of time is not likely to be a signature of speculation. Speculation can and does drive the price in the short-run, but not the long-run."

The second conclusion results from the assumption of a one-period-increase in the expected future price. If one assumes instead that that price expectations rise over an extended period of time (as in the case of a bubble), then also spot prices would keep rising and departing from the fundamental equilibrium (in the context of Thoma's stock-flow-model). At the same time, however, inventories would rise accordingly, due to the widening disequilibrium in the flow market.

According to Frankel such an increase in inventories needs not to take place in the "real world". The reason is simple: The cheapest way to store a commodity like oil is leaving it underground. If, e. g., an increase in expected future prices of oil or a fall in interest rates induce a supplier to raise his stock of oil relative to previous plans, then he will simply postpone part of the extraction (Frankel, 2008; see also his postings on http://content.ksg.harvard.edu/blog/jeff_frankels_weblog). In the context of Thoma's model, such a form of "inventory accumulation" implies a shift of the flow-supply-schedule to the left: Spot prices rise but (above ground) inventories do not.

Frankel underlines the importance of keeping inventories underground by reducing current supply for the following reason: He considers the loose monetary policy and the related abnormally low level of interest rates in recent years to be the most important single reason for the price rise of key commodities, notably of crude oil. The decline in returns on financial assets reduced the (opportunity) costs of keeping oil underground. As consequence, growth of oil supply lagged behind the growth of demand, pushing oil prices up.

The explanation of rising commodity prices by Krugman and Thoma as well as the explanation by Frankel share the belief that prices are driven by fundamentals. They differ insofar from each other as rising inventories would point to destabilizing speculation in the context of the Krugman-Thoma-approach, but not in the context of Frankel's explanation (in his case rising inventories could also be the result of a decline in interest rates when commodities cannot be stored underground).

In the following case, the price of a commodity follows the moving intersection of supply and demand schedules in the spot (flow) market, and yet, one would hardly conceive the price movement as driven by fundamentals. This case fits well the "bull-bear-hypothesis". The market for crude oil during the recent price boom is taken as example:

- For lack of a global market place where physical oil could be directly exchanged at an world spot price, buyers and sellers of oil agree to take the oil futures price of the nearby contract (i.e., the contract which is next to expire) prevailing at the day of delivery as spot price (as is actually the case as shall later be documented).
- Oil suppliers like OPEC countries have therefore no control over prices; however, they can control oil supply to a substantial extent.
- Financial investors drive oil prices up in the futures markets. OPEC countries and other suppliers adjust output to the (slight) slow-down in oil demand. Hence, there is neither an excess supply nor any shortage in the spot/flow market for oil.
- The situation is optimal for producers/owners of crude oil: The oil price increase means a revaluation of the total stock of oil, at the same time the speed of depletion of this exhaustible "treasure" is dampened, and, finally, producers cannot be blamed for high energy costs. This is so because the price of oil is determined in a (very) free market, namely, the market for crude oil derivatives.[6])
- In this situation, OPEC can easily promise to provide the oil-importing countries with unlimited supply (at the prevailing price), and it will blame speculators for driving oil prices up in the derivatives markets.
- The rise in oil prices and in commodity prices in general pleases financial investors who had opened huge long positions in commodity derivatives. The profits from these positions increase enormously due to high leverage factors (exceeding 15 in most cases).
- However, these "investors" are not per se interested in a high level of asset prices but in persistent trends. Hence, only during the oil bull market did the interests of oil suppliers and of financial investors coincide. The opposite will become evident once more and more investors, in particular hedge funds, will bet on a commodity bear market.

[6]) On theoretical grounds, one should note that the empirical coincidence of the real oil price rising at a rate persistently higher than the (risk-free) rate of interest and stagnant oil production contradicts the Hotelling rule, derived from the neo-classical model of price determination of exhaustible resources (Hotelling, 1931). According to the Hotelling model such a price increase should induce an increase in supply which would in turn bring price movements back on the equilibrium path.

One can summarize the different theoretical concepts concerning the relationship between supply and demand in the stock and flow markets for commodities, spot and futures commodity prices and inventory accumulation as follows:

- In the models of Krugman and Thoma, the causality runs from changes in supply and demand conditions in the markets for the physical commodity to price movements. If also destabilizing speculation is in effect, it must show up in rising inventories. Long-term commodity price trends can therefore not be caused by destabilizing speculation.
- In Frankel's model, the causality runs primarily from falling interest rates to higher demand for inventories. This demand will in many cases be met by reducing supply, i.e., by increasing invertories "underground". Since this is not always possible, higher inventories "above ground" do not necessarily indicate destabilizing speculation.
- In the alternative "bull-bear-hypothesis" as sketched in the present study, the causality runs from price movements in the futures markets (driven at least in part by speculation) to spot prices. Monopolistic suppliers adjust to higher spot prices by reducing their supply of the (physical) commodity to that level which is demanded for at the higher price.

Which observations concerning supply, demand and inventories in the markets for physical commodities would fit the "fundamentalist hypothesis", and which would be rather in line with the "bull-bear-hypothesis"?

No clear theoretical relationship exists between price movements and inventories in the case of exhaustible commodities which can be "stored" underground. As regards other commodities, a simultaneous increase in prices and inventories would indicate destabilizing speculation in the context of the Krugman-Thoma-approach. However, if at the same time interest rates are falling to or staying at an abnormally low level, the price rise could also be attributed to fundamentals in the context of Frankel's model.

With respect to the medium-term development of demand for and supply of physical commodities, the (empirical) coincidence of an increasing growth of world consumption, a declining growth of world production, and a (very) strong rise in the price of the respective commodity would give support to the "fundamentalist hypothesis". However, such a coincidence would not contradict the "bull-bear-hypothesis" since this explanation holds that both, fundamentals as well as (destabilizing) speculation, drives commodity prices. Hence, a comparison of the empirical relevance of both explanations necessitates also an – albeit imprecise - evaluation of how strongly the price of a commodity rose relative to the changes in the growth of demand and supply.

The (empirical) coincidence of strongly rising commodity prices with a decline in demand growth and an even stronger decline in supply growth would rather support the "bull-bear-hypothesis" as compared to the "fundamentalist hypothesis". This is so because if world prices rise strongly and persistently, one would expect a significant acceleration of global demand if fundamentals are to be considered the driving force.

I shall now briefly discuss the relationship between spot and futures prices in commodities markets, taking crude oil as example.

5. Relationship between spot and futures prices in commodities markets

Textbook economics holds that any futures price is derived from the prevailing spot price which in turn is determined by market fundamentals. Hence, the following relationships hold: First, the futures price is the spot price plus the total storage cost ("cost of carry"), mainly the rate of (foregone) interest. Second, in an efficient market, the spot price is determined by demand for and supply of the physical commodity. If destabilizing speculation drives the price up, then this inefficiency must show up in rising inventories of the respective commodity.

According to this logic, price movements in futures markets do not matter for spot prices, and a price boom of the latter can only be due to destabilizing speculation if inventories rise at the same time. As Krugman put it: "Buying a futures contract for oil *does not* reduce the quantity of oil available for consumption."[7])

However, this logic - derived from theoretical assumptions - does not characterize the empirical relationships for two reasons. First, a change in oil consumption is neither a necessary nor a sufficient condition for the emergence of (hypothetical) spot price changes as such a change can be compensated by a change in "underground inventories". Second (and more important), in commodities markets the prevailing futures price is taken as benchmark for the spot price. This is particularly true for the crude oil market: "Most crude oil is traded based on long-term contracts, and the prices in those contracts are set by a system known as 'formula pricing'. In this system, the price of delivered crude is set by adding a premium to, or subtracting a discount from, certain benchmark or marker crudes, namely: West Texas Intermediate (WTI), Brent and Dubai-Oman. Generally, WTI is used as the benchmark for oil sold to North America, Brent for oil sold to Europe and Africa, and Dubai-Oman for Gulf crude sold in the Asia-Pacific market."[8])

Fattouh (2007, p. 5) explains why pricing physical crude has shifted to use futures prices as benchmark since the late 1980s: "The declining liquidity of the physical base of the reference crude oil and the narrowness of the spot market have caused many oil-exporting and oil-consuming countries to look for an alternative market to derive the price of the reference crude. The alternative was found in the futures market. When formula pricing was first used in the mid-1980s, the WTI and Brent futures contracts were in their infancy. Since then, the futures market has grown to become not only a market that allows producers and refiners to hedge their risks and speculators to take positions, but is also at the heart of the current oil-pricing regime. Thus, instead of using dated Brent as the basis of pricing crude exports to

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[7]) http://krugman.blogs.nytimes.com/2008/06/21/calvo-on-commodities/).

[8]) http://peakoildebunked.blogspot.com/2008/07/366-futures-prices-determine-physical.html

Europe, several major oil-producing countries such as Saudi Arabia, Kuwait and Iran rely on the IPE Brent Weighted Average (BWAVE)".[9])

The key role of crude oil futures prices in the process of spot price determination is documented more in detail in *Mabro* (2005) and *Fattouh* (2006). The conclusion is straightforward: Even though the level of the spot price of a specific crude oil differs from the futures price of the "marker crude" (depending on quality differences), the movements of crude oil spot prices are driven by the price movements in the futures markets of the respective "marker crude" (predominantly Brent and WTI).

Physical agricultural commodities differ much more in their specific qualities than crude oil. Moreover production and, hence, trading of agricultural commodities is regionally more dispersed in the global economy than the supply and trading of crude oil. At the same time there exists just one dominating futures market for the most important agricultural commodities like, the Chicago Board of Trade (CBOT). One can therefore presume that the prices determined in this highly liquid market serve as benchmarks for pricing agricultural commodities in the spot markets (even if there is no "formula pricing" as in the case of the crude oil market).

As futures prices serve as benchmarks for commodities prices, expectations formation and transaction behaviour of participants in futures markets impact directly on the determination of commodities prices. The "fundamentalist hypothesis" assumes that rational actors form their price expectations according to the supply and demand conditions in the market for the respective physical commodity, hence, only the fundamentals matter.

By contrast, the "bull-bear-hypothesis" holds that the formation of commodities prices is also influenced by non-fundamental factors. This is so because this hypothesis assumes that price dynamics in any highly traded futures market is driven by the interaction of news-based traders, technical traders and "late coming bandwagonists" (usually amateurs). Most of the time there operates an "expectational bias" in favour or against the respective asset. If an optimistic bias ("bullishness") prevails, traders put more money into a long position than into a short position and hold it longer than a short position (and vice versa in the case of a "bear market"). This behaviour causes an upward (downward) trend to develop over several months or even years.

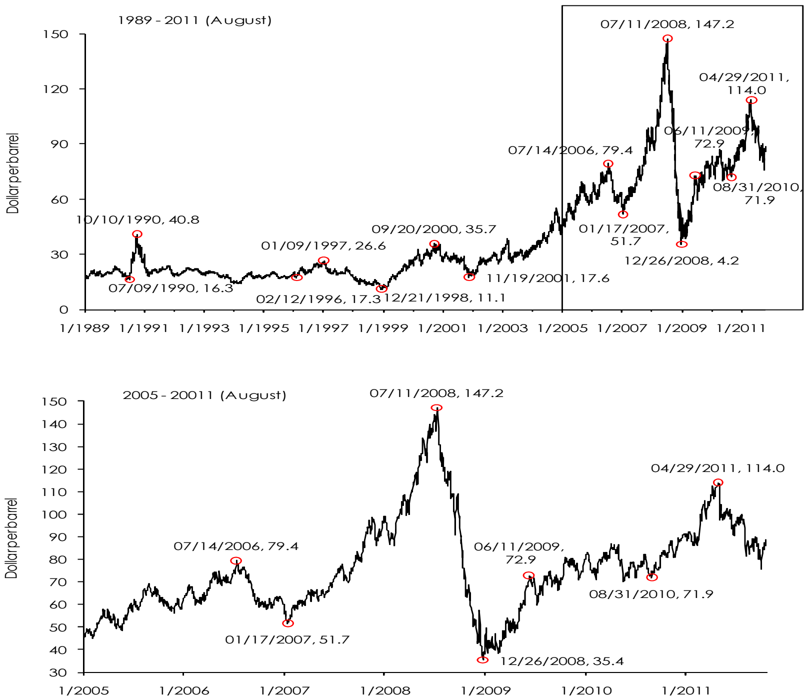
[9]) BWAVE is an average of all futures price quotations for a given contract during a trading day. This price serves as benchmark for the spot price (formula) in long-term oil contracts. Note, that the International Petroleum Exchange (IPE), the London-based oil futures exchange was taken over by the Intercontinental Exchange (ICE) in 2005. Hence, ICE is the leading market place for trading Brent oil futures as NYMEX is the leading exchange for trading WTI oil futures.

6. Empirics of commodity price fluctuations

Figures1 and 4 to 7 show that daily commodity futures prices fluctuate strongly, however, most of the time they move along "underlying" trends which last for several months or even for years. These long-term trends of rising or falling prices are called "bull markets" or "bear markets" in the traders' jargon (the time horizons in financial markets are generally shorter than in goods markets, hence, several months represent the long run).

In the oil futures market, e. g., the invasion of Kuwait by Iraqi troops triggered a "bull market" in early July 1990, the oil price rose from 16.3 $ to 40.3 $ (October 9, 1990). The price declined again during a short "bear market", in particular during the liberalization of Kuwait ("desert storm") in January 1991, when the oil price fell to 20.1 $ (figure 4). A typical "bull market" took place between February 1999, and September 2000 (the oil price more than tripled, rising from 11.5 $ to 35.7 $), followed by a "bear market" during which the price fell to 17.6 $ in November 2001. High economic growth in 1999 and the first half of 2000 contributed to a strong upward trend, the subsequent downward trend was strengthened by the recession in the advanced economies as well as by the terrorist attack of September 11, 2001.

Figure 4: Dynamics of oil futures prices
Daily price of the most traded WTI crude oil futures contract (NYMEX)



Source: New York Mercantile Exchange (NYMEX).

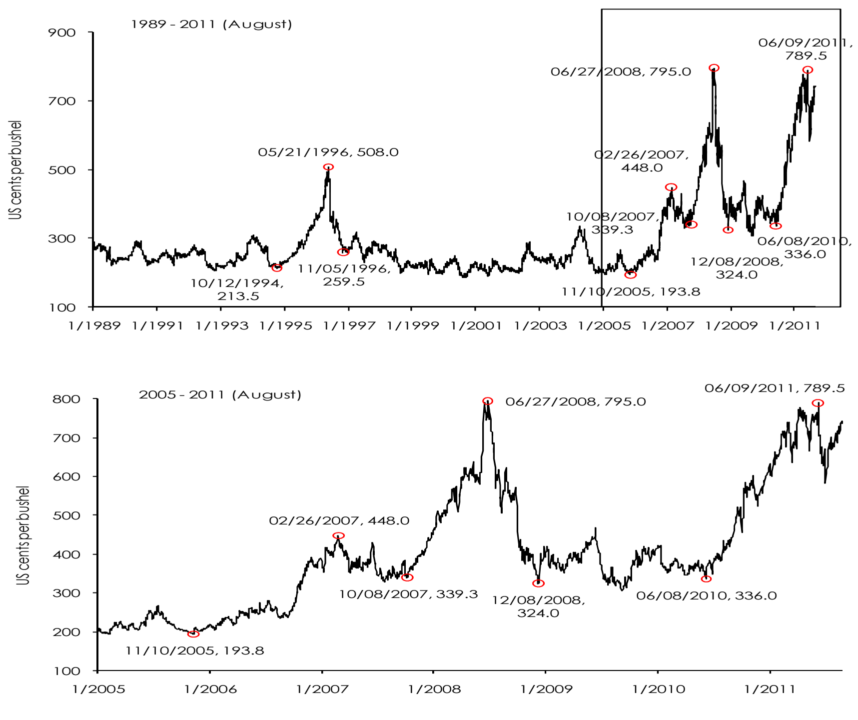
These examples show that asset price trends are always related to developments in the real economy, however, the persistence of the price movements might be strengthened also by non-fundamental factors, in particular by trend-following trading practices based on technical analysis.

In comparison to the bull market of oil prices which took off in 2002 and which got exceptionally strong during the first half of 2008, the long-term upward and downward trends taking place during the 1990s seem minor events (figure 4). One should, however, keep in mind, that also these minor "bulls" and "bears" involved strong price movements. E g., during 1996 oil prices almost doubled, over the two subsequent years prices fell strongly, down to 11.2 $ by the end of 1998 (figure 4).

Between January 2007 and July 2008 oil prices almost tripled without any tremendous supply or demand shock toking place (figure 4). In 1973/74 and 1979/80 oil prices had also roughly tripled, yet, these episodes had been shaped by "shocking" events like the Yom-Kippur war and the subsequent (alleged) oil boycott by Arabic countries (1973) as well as the coming to power of the Ayatollahs in Iran and the subsequent Gulf war (1979/80). The oil price boom 2007/2008 was followed be the strongest bear market of oil prices in post-war history (figure 4).

Figure 5: Dynamics of corn futures prices

Daily price of the most traded corn futures contract (CBOT)



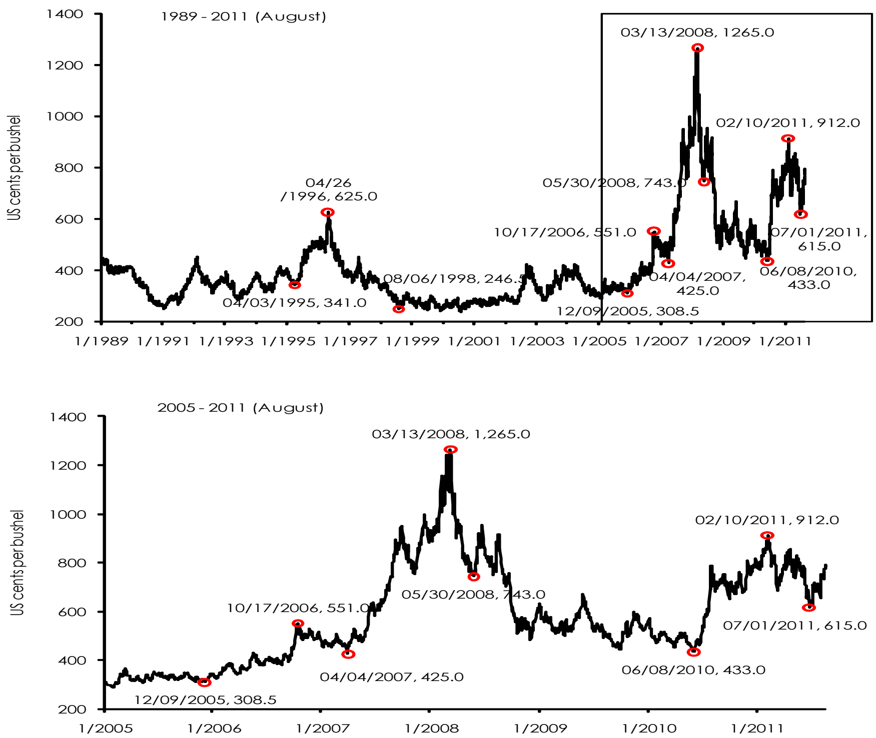
Source: Chicago Board of Trade (CBOT)

In two shorter bull markets between end-2008 and mid-2009 and between August 2010 and April 2011 oil prices rose again from 35 $ to 114 $ (figure 4). Since then oil prices have again come down, not the least due to the slow-down in global economic growth (the WTI oil price stays at 96 $ at the end of August 2012, the price for Brent at 114 $ - the latter is usually by roughly 15 $ higher than the former).

Figures 5 to 7 show that also futures prices of corn, wheat and rice fluctuate most of the time around "underlying" trends. In order to understand how the sequence of short-term upward and downward price runs (monotonic price movements) accumulates to a long-term trend, one has to consider the following. Any bull market (bear market) can be brought about in two different ways (or a combination of both): In the first case upward (downward) runs are steeper than "counter-runs", in the second case upward (downward) runs last longer than "counter-runs".

Figure 6: Dynamics of wheat futures prices

Daily price of the most traded wheat futures contract (CBOT)

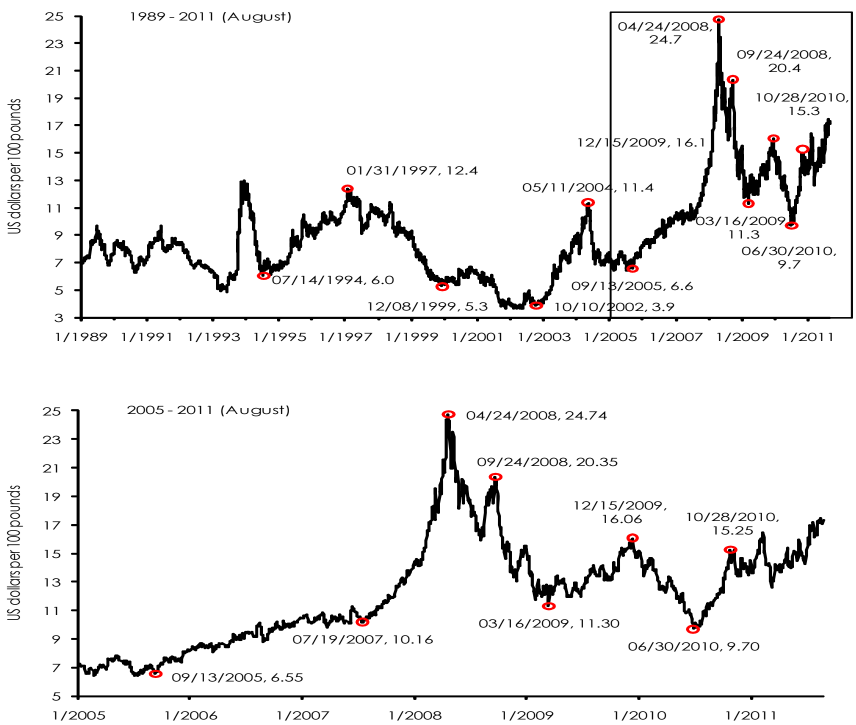


Source: Chicago Board of Trade (CBOT)

A close inspection of daily commodity price movements – taking the most recent boom as example – suggests the following hypothesis (see figures 4 to 7). A long-term upward (downward) trend (bull and bear market, respectively) is primarily the result of the accumulation of upward (downward) price runs (monotonic movements) which last for many months or even for some years longer than the counter-movements. In other words, the overall price increase (decrease) is not exclusively brought about by upward (downward) runs being steeper than downward (upward) runs (as would be the case if news cause prices to jump instantaneously to their new fundamental equilibrium values). It is this persistence of short-term trends being in line with the "bullish" or "bearish" market sentiment which technical models try to exploit (these models do not aim at "riding" the long-term trend as a whole but to jump on the single short-term trends which cause the price to appreciate in a stepwise process).

Figure 7: Dynamics of rough rice futures prices

Daily price of the most traded rough rice futures contract (CBOT)



Source: Chicago Board of Trade (CBOT)

In order to examine this hypothesis, the following exercise is carried out. First, I identify the most pronounced bull markets and bear markets which occurred over the past 20 years in the four futures markets investigated (in addition to the most recent bull market, two bull markets and two bear markets" are – somewhat arbitrarily – selected – see table 1 and figures 4 to 7). As next step, I explore how the accumulation of monotonic movements ("runs") of daily futures prices brings about price trends lasting many months or even several years.

Table 1: Runs of commodity futures price during "bull markets" and "bear markets"

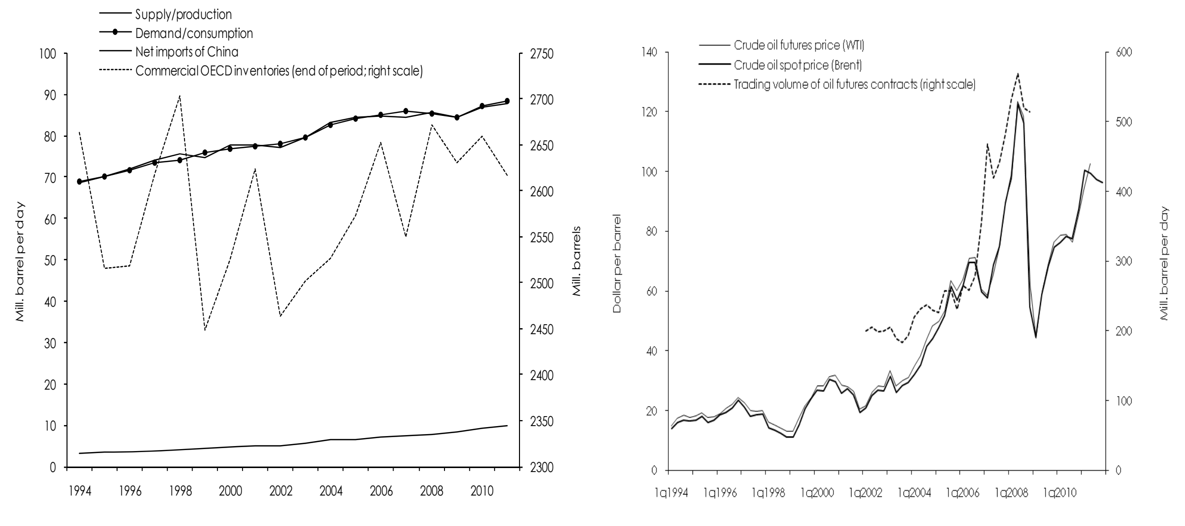
		Upward runs			Downward runs		
Period		Number	Average durations in days	Average slope	Number	Average durations in days	Average slope
				Based on original data			
Oil [1])	12/21/1998 - 09/20/2000	101	2.50	1.44	100	1.77	-1.43
	09/20/2000 - 11/19/2001	71	2.01	2.12	72	1.96	-2.67
	11/19/2001 - 07/14/2006	285	2.21	3.18	284	1.77	-3.52
	07/14/2006 - 01/17/2007	31	1.52	3.28	32	2.38	-3.79
	01/17/2007 - 07/11/2008	91	2.32	4.23	91	1.75	-3.89
	07/11/2008 - 12/26/2008	26	1.62	6.62	27	2.70	-8.99
	12/26/2008 - 06/11/2009	28	2.14	4.06	27	1.96	-3.81
	08/31//2010 - 04/29/2011	32	2.09	2.46	31	2.10	-1.81
Corn [2])	10/12/1994 - 05/21/1996	100	2.14	1.15	100	1.64	-0.97
	05/21/1996 - 11/05/1996	29	1.69	2.12	30	2.17	-2.49
	11/10/2005 - 02/26/2007	82	1.88	0.51	81	1.95	-0.39
	02/26/2007 - 10/08/2007	39	1.95	0.60	40	1.90	-0.76
	10/08/2007 - 06/27/2008	49	2.14	0.74	48	1.54	-0.63
	06/27/2008 - 12/08/2008	30	1.43	0.92	31	2.13	-1.19
	06/08/2010 - 06/09/2011	61	2.30	0.62	60	1.78	-0.61
Wheat [2])	04/03/1995 - 04/26/1996	68	2.16	3.78	67	1.64	-3.43
	04/26/1996 - 08/06/1998	143	1.71	2.81	144	2.16	-3.03
	12/09/2005 - 10/17/2006	48	2.31	0.63	47	2.09	-0.54
	10/17/2006 - 04/04/2007	26	1.62	0.82	27	2.52	-0.72
	04/04/2007 - 03/13/2008	58	2.14	1.63	57	1.88	-1.32
	03/13/2008 - 05/30/2008	12	1.58	1.48	12	2.75	-2.14
	06/08/2010 - 02/10/2011	49	2.00	0.74	48	1.50	-0.73
	02/10/2011 - 07/01/2011	23	1.61	0.86	24	2.38	-0.85
Rice [1])	07/14/1994 - 01/31/1997	162	1.57	3.72	161	1.78	-3.86
	01/31/1997 - 12/08/1999	168	1.86	3.38	168	2.24	-3.39
	10/10/2002 - 05/11/2004	90	2.24	1.33	89	1.98	-1.19
	05/11/2004 - 09/13/2005	80	1.83	0.97	81	2.12	-1.16
	09/13/2005 - 04/24/2008	153	2.10	0.96	152	2.09	-0.70
	09/24/2008 - 03/16/2009	27	1.74	1.55	28	2.46	-1.86
	03/16/2009 - 12/15/2009	45	2.33	0.96	44	1.84	-0.93
	12/15/2009 - 06/30/2010	29	1.55	0.91	30	2.47	-1.07
	06/30/2010 - 10/28/2010	18	2.61	1.04	18	1.33	-0.82
				Based on 5 days moving average			
Oil [1])	21/12/1998 - 09/20/2000	37	7.41	0.70	36	4.19	-0.56
	09/20/2000 - 11/19/2001	29	4.59	0.88	29	4.97	-1.18
	11/19/2001 - 07/14/2006	99	6.72	1.42	98	4.49	-1.57
	07/14/2006 - 01/17/2007	11	2.91	1.17	11	7.82	-1.82
	01/17/2007 - 07/11/2008	36	6.36	2.20	35	3.89	-1.64
	07/11/2008 - 12/26/2008	7	3.43	2.69	8	10.88	-4.79
	12/26/2008 - 06/11/2009	11	5.73	1.62	10	4.60	-1.68
	08/31//2010 - 04/29/2011	13	6.15	1.14	12	4.00	-1.01
Corn [2])	10/12/1994 - 05/21/1996	40	6.25	0.49	39	3.13	-0.33
	05/21/1996 - 11/05/1996	8	4.13	0.99	9	7.60	-1.10
	11/10/2005 - 02/26/2007	35	5.00	0.21	35	3.80	-0.16
	02/26/2007 - 10/08/2007	19	3.68	0.22	20	3.90	-0.31
	10/08/2007 - 06/27/2008	20	6.25	0.34	19	2.63	-0.25
	06/27/2008 - 12/08/2008	11	2.45	0.42	11	7.00	-0.60
	06/08/2010 - 06/09/2011	28	5.57	0.26	28	3.07	-0.23
Wheat [2])	04/03/1995 - 04/26/1996	29	5.38	1.69	29	3.28	-1.08
	04/26/1996 - 08/06/1998	53	3.75	1.04	53	6.38	-1.26
	12/09/2005 - 10/17/2006	13	8.85	0.32	12	7.50	-0.24
	10/17/2006 - 04/04/2007	16	2.75	0.22	17	3.65	-0.32
	04/04/2007 - 03/13/2008	26	5.38	0.65	23	3.70	-0.45
	03/13/2008 - 05/30/2008	4	1.75	0.33	5	8.20	-0.94
	06/08/2010 - 02/10/2011	19	5.32	0.36	18	3.61	-0.27
	02/10/2011 - 07/01/2011	8	4.25	0.31	9	6.22	-0.44
Rice [1])	07/14/1994 - 01/31/1997	64	5.05	1.65	62	4.29	-1.68
	01/31/1997 - 12/08/1999	73	3.81	1.41	76	5.20	-1.55
	10/10/2002 - 05/11/2004	36	5.75	0.64	37	4.46	-0.45
	05/11/2004 - 09/13/2005	24	4.75	0.47	25	7.92	-0.54
	09/13/2005 - 04/24/2008	62	5.92	0.43	61	4.28	-0.30
	09/24/2008 - 03/16/2009	9	4.00	0.70	10	7.60	-0.97
	03/16/2009 - 12/15/2009	23	4.39	0.48	23	3.48	-0.36
	12/15/2009 - 06/30/2010	11	3.36	0.33	11	6.91	-0.59
	06/30/2010 - 10/28/2010	8	6.63	0.54	6	2.17	-0.18

[1]) Average change in price level per day in cents.

Table 1 shows that the upward trend of oil futures prices which took place between January 17, 2007, and July 11, 2008, was primarily due to upward runs lasting by one third longer than downward runs (2.32 days versus 1.75 days), the average slope of upward runs was just by roughly 10% greater than the average slope of downward runs. This pattern is particularly pronounced on the basis of 5-days moving averages of the original price series (table 1).

If one examines the pattern of accumulation of price runs for all cases comprised in table 1, it turns out that in only 4 out of 62 cases are upward (downward) runs not longer than downward (upward) runs during an "bull market" ("bear market"). Hence, the persistence of short-term price movements and their different length contributes to the phenomenon of long-term trends in commodity futures markets (this result was already obtained in a study which elaborated the pattern of exchange rate dynamics by measuring the path of the daily deutschemark/dollar exchange rate between 1980 and 1986 – see *Schulmeister*, 1987).[10]) Technical trading systems try to exploit this pattern of asset price dynamics and by doing so strengthen it in turn (as shall later be demonstrated).

Figure 8: World market for crude oil, oil futures trading and oil price movements



Source: Energy Information Agency (EIA), OECD, New York Mercantile Exchange (NYMEX), Intercontinental Exchange (ICE).

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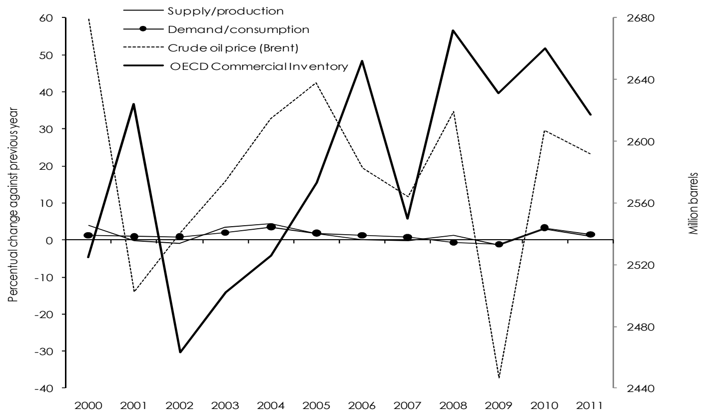
10) In a study on the dynamics of the $/€ exchange rate I quantify the relationship between short-term runs and long-term trends of asset prices across different data frequencies (Schulmeister, 2008B). It turns out that the sequence of persistent price movements - interrupted by comparatively short lasting counter-movements - can be observed on every time scale: Several runs based on minutes or five minutes data which last in one direction longer than the counter-movements, add up to one trend based on hourly data, many hourly trends add up to one trend based on daily data, several daily trends result in one long-term trend. Since the phenomenon of "trending" repeats itself across different time scales, technical traders use price data of different frequencies (increasingly intraday data). At the same time, the use of these trading systems feeds back upon the persistence of the trends.

7. Market fundamentals: Supply and demand conditions in commodity spot markets

This chapter compares the development of supply of and demand for (physical) crude oil, corn, wheat and rice in the world spot markets and the related changes in inventories, to the movements of the respective futures prices.[11]) Such a comparison should help to evaluate the plausibility of the "fundamentalist hypothesis", namely, that futures prices reflect exclusively - at least primarily - the (expected) changes in market fundamentals.

Global supply (production) of crude oil rose by 1.5 % per year between 1994 and 2002, slightly slower than global demand (+1.8 % - figure 8). Hence, global commercial oil inventories declined by 199 mill. barrels between 1994 and 2002 (end of years). Over this period oil futures prices rose comparatively modestly, namely, from 17.1 $ in 1994 to 26.0 $ in 2002 (annual averages).

Figure 9: World market for crude oil



Source: Energy Information Agency (EIA), OECD.

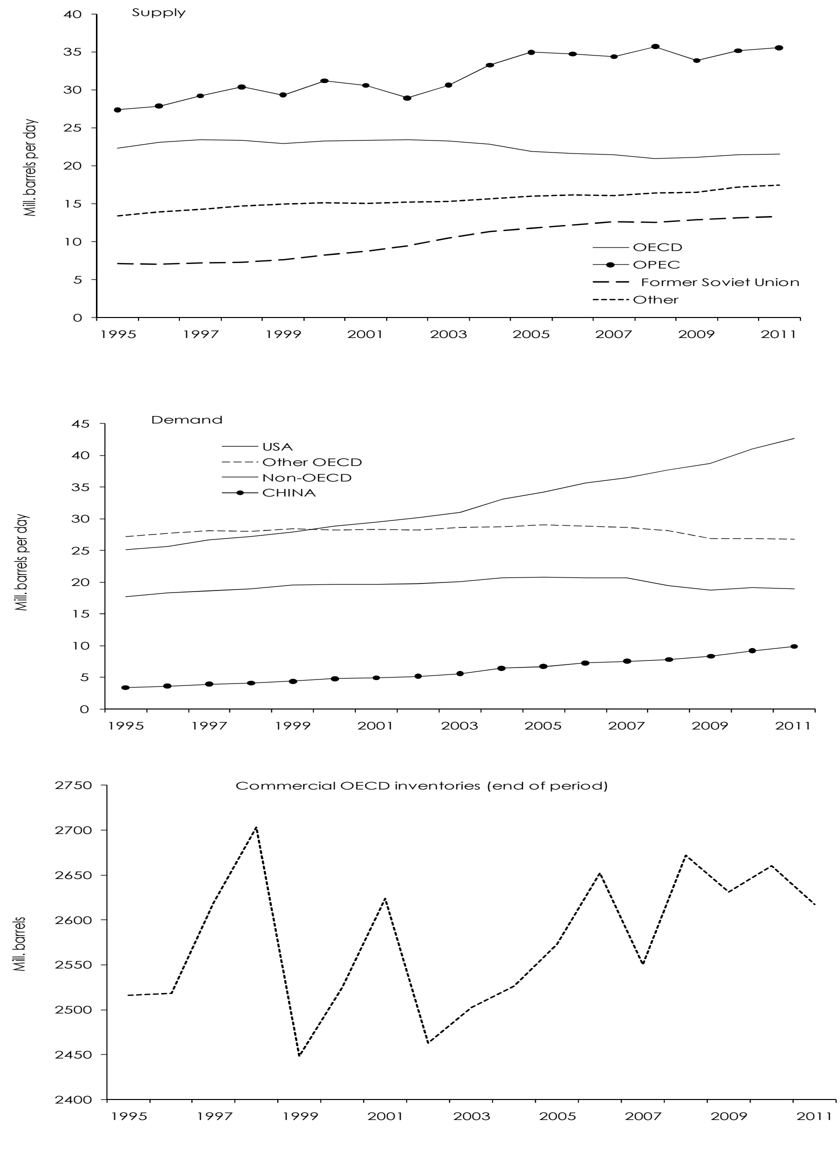
Over the three subsequent years, oil production expanded slightly faster than oil consumption, causing inventories to rise by 200 mill. barrels between 2002 and 2006 (figure 8). In spite of this rise in (buffer) stocks, oil prices increased strongly between 2002 and 2006, namely, from 26.0 $ to 66.7 $.

Between the beginning of 2007 and mid 2008 the oil price boom accelerated significantly, over these 18 months futures prices rose from 51.7 $ to 147.2 $ (figure 4). This development can hardly be explained by the conditions in the market for physical crude oil. Even though

[11]) The price of the most traded contract is taken as benchmark for futures prices. This is the near-by contract (the contract which is next to expire) until (roughly) the 10th day of the expiration month. For crude oil, prices are those of the WTI crude oil contract traded at the New York Mercantile Exchange (NYMEX), for corn, wheat and (rough) rice futures prices of the respective contracts traded at the Chicago Board of Trade (CBOT) are used.

global commercial oil reserves declined between the end of 2006 and the end of 2007 (over both years demand grew slightly stronger than supply – figure 9), this decline seems much too small to account for the extent of the oil price rise. This becomes clear if one compares the decline in commercial inventories between 2006 and 2007 to their increase over the preceding 4 years (figure 8).

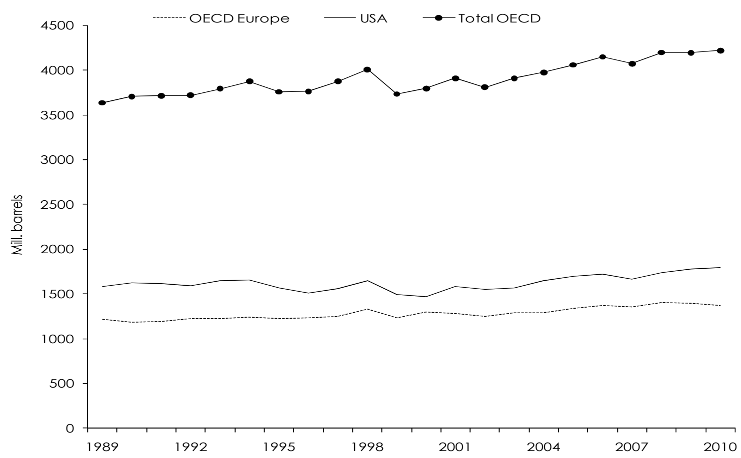
Figure 10: Global supply of and demand for crude oil



Source: Energy Information Agency (EIA).

The spectacular oil price boom over the first half of 2008 (futures prices climbed by 60 $ - figure 4) coincided with a slow-down of global economic growth and a continuous deterioration of the prospects for the near future (due to the financial crisis as well as the rise in commodities prices and, hence, in headline inflation). At the same time, oil production picked up relative to demand so that inventories rose in the course of 2008 (figures 8 and 9). It seems therefore very hard to interpret this last phase of the oil price boom as primarily determined by market fundamentals (at least in the hindsight it becomes clear that Paul Krugman and Mark Thoma were just assuming that oil inventories would be constant or even declining).

Figure 11: Total crude oil inventories in OECD countries1)



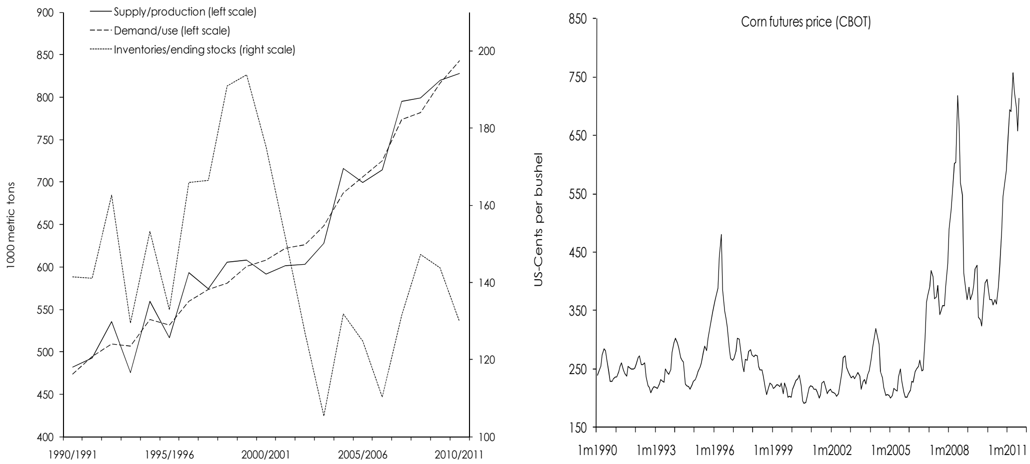
1) Including strategic reserves.
Source: Energy Information Agency (EIA).

It is often argued that oil demand from emerging market economies, in particular from China, has strongly contributed to the global oil price boom. However, this assertion is not warranted by the facts. First, China accounts for only 9% of global demand (figure 10). Second, China still produces roughly half of its overall oil consumption. Third, China's demand for crude oil has expanded very continuously over the past 15 years. Hence, the economic boom in China can hardly explain the extent of oil price fluctuations, in particular the boom between 2002 and 2008 (figures 4 and 10).

Figure 9 displays the (small) annual percentage changes of supply of and demand for crude oil on the one hand, and the (big) changes in the price of crude oil on the other hand. The huge difference between the rate of change of the fundamentals and the oil price sheds serious doubts on the assessment that the oil price boom and its acceleration since 2007 can entirely be explained by market conditions.

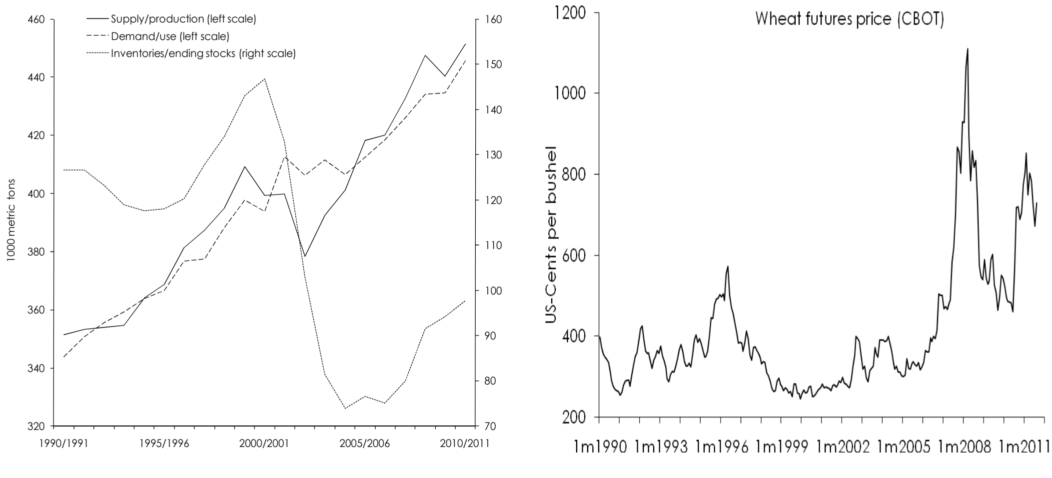
Figure 10 shows global supply (production) of and demand (consumption) for crude oil by country groups. Over the past 15 years or so, the increase in demand has originated exclusively from emerging market economies, demand of advanced economies (OECD countries) has been stagnating or even declining (since 2007). Over the same period, the increase in supply of OPEC, the former USSR and other countries has overcompensated for the decline in oil production in OECD countries. As a consequence, supply has been growing somewhat stronger than demand so that global inventories rose: Including the strategic reserves, they have increased since 1999 by almost 500 mill. barrel (figure 11)

Figure 12: World market conditions for corn and corn futures price movements



S: U.S. Department of Agriculture, CBOT.

Figure 13: World market conditions for wheat and wheat futures price movements

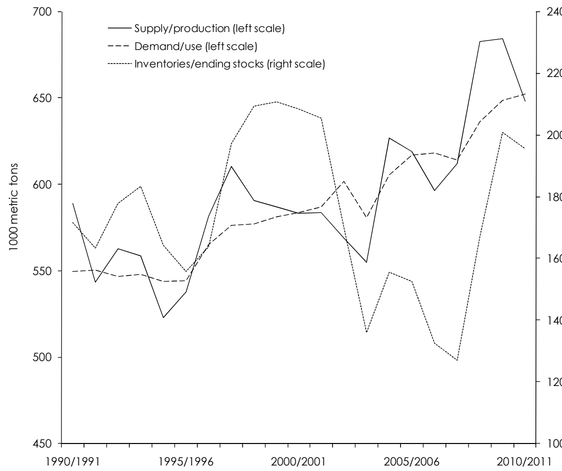


Source: U.S. Department of Agriculture, CBOT.

A comparison between supply and demand conditions in the spot markets for corn, wheat and rice on the one hand, and the development of the respective futures prices does also raise doubts about the relevance of the "fundamentalist hypothesis". Between the marketing periods 1999/2000 and 2003/2004, global inventories of these commodities strongly declined ("marketing periods" of agricultural commodities begin "around" the mid of a calendar year – they differ across commodities). Yet, over this period as well as over the subsequent two years, prices of corn, wheat and rice did not rise substantially (figures 12 to 14). The price boom of these commodities took off only around mid-2007 when global production grew actually stronger than consumption (with the exception of rice, however, the gap between demand and supply has been narrowing also in this case – figures 10 to 12).

Also the almost simultaneous and strong increase in the prices of corn, wheat and rice since mid-2010 (figures 5 to 7) can hardly be explained by changes in demand and supply conditions in the spot markets (figures 12 to 14).

Figure 14: World market conditions for rice and rice futures price movements



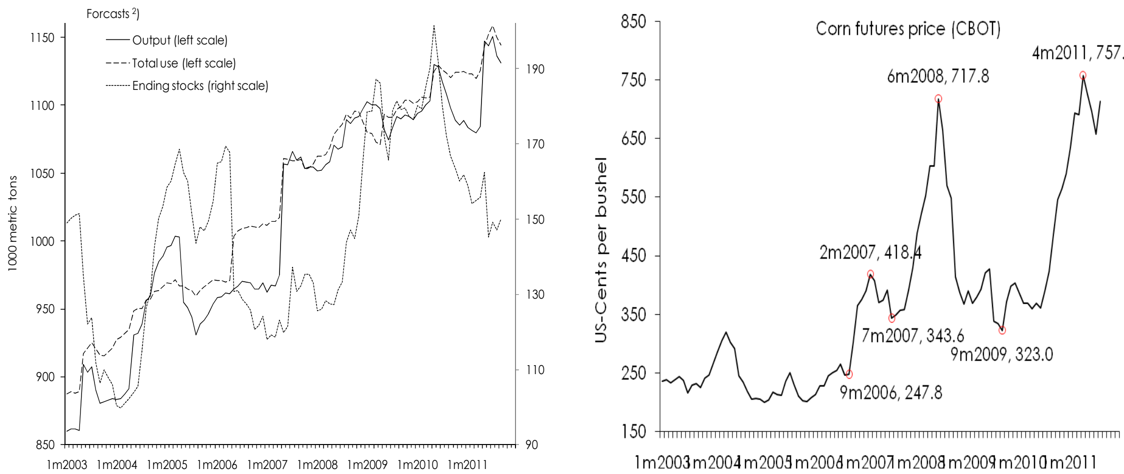
Source: U.S. Department of Agriculture, CBOT.

The "fundamentalist hypothesis" implies that traders in commodity futures markets form their expectations according to the future development of supply and demand in the underlying spot markets. Hence, one should presume that traders take into account the most recent forecasts of experts in the different markets for agricultural commodities. In order to investigate this issue, figures 15 to 17 compare the monthly "World Supply and Demand Estimates" (WASDE) of the "World Agricultural Outlook Board" of the U.S. Department of Agriculture for coarse grain (corn is the by far most important component of this group of cereals), wheat and rice to the movements of the respective futures prices. The forecasts used in this study refer to the current marketing year (for wheat, e. g., the marketing year starts on June, 1; hence, the WASDE wheat forecast published in September 2007 refers to market conditions prevailing over the period June 1, 2007, to May 31, 2008).

In early 2006, WASDE started to revise their forecast of coarse grain consumption upwards, and, hence, of global inventories downwards. With some lag, corn futures prices picked up in September 2006 (figure 15). The subsequent decline in corn futures prices might have been related to the simultaneous upward revisions of coarse grain stocks. However, when WASDE started to gradually increase their forecasts of inventories in February 2008, corn futures prices kept booming until mid-2008 (figures 5, 13).

In May 2010, WASDE started to revise their forecast of coarse grain inventories downwards. This time, the subsequent increase in the price of corn was in line with this revision, even though the extent of the price rise – the corn futures price more than doubled between June 2010 and June 2011 – might also be due to increased speculation (trading volume also strongly increase in that period – figures 5, 15, 22).

Figure 15: Forecasts of world market conditions for coarse grains1) and corn futures price movements

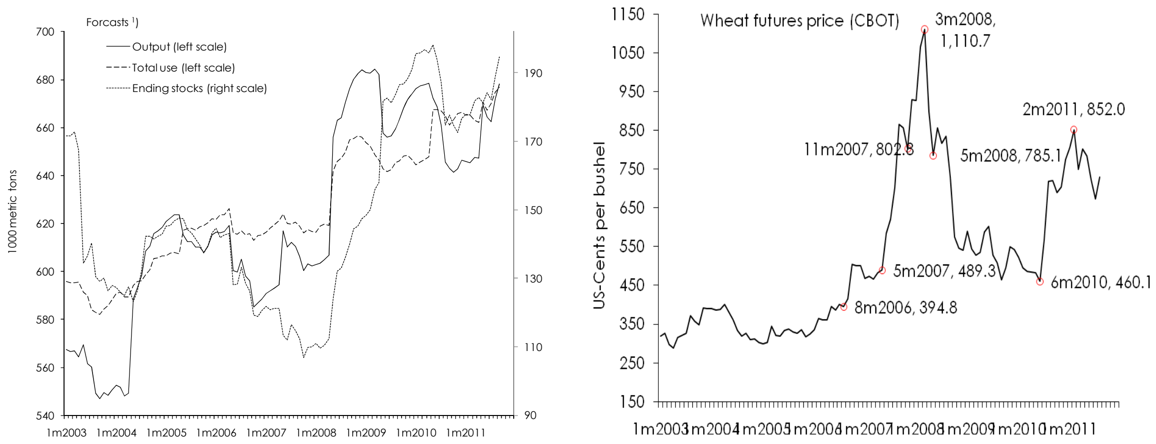


1) Primarily corn. 2) Monthly forecasts of market conditions in the current marketing year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

A comparison between WASDE projections for wheat and the development of wheat futures prices shows a similar picture (figure 16). Until October 2007, the rise in wheat prices was in line with the steady downward revisions of WASDE forecasts of global wheat inventories. However, the wheat futures price boom continued until March 2008, in spite auf gradual upward revisions of global production and stocks of wheat. Only when WASDE changed the outlook sharply to the better in March 2008 (forecasting an excess supply instead of demand) did wheat futures prices react immediately and began to fall (figure 16).

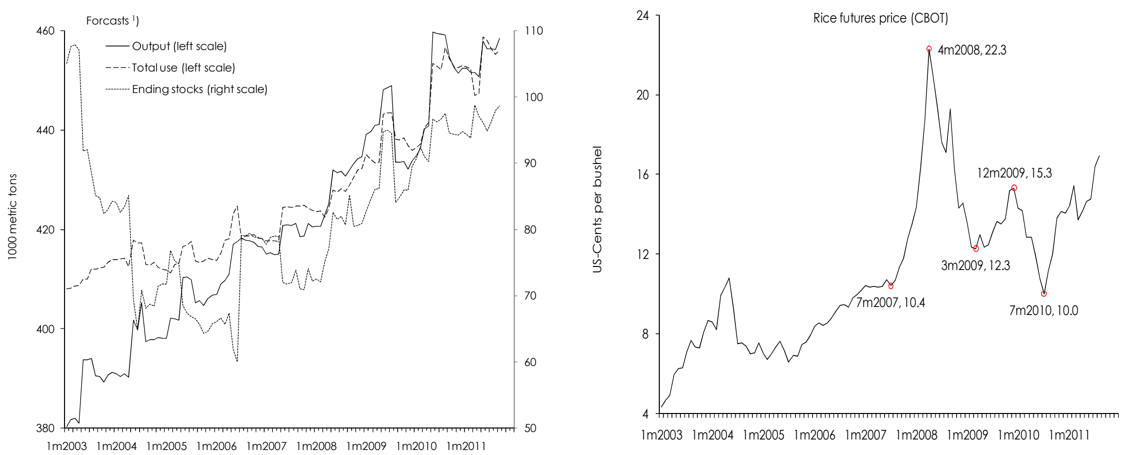
In May 2010, WASDE projected also a decline in global wheat inventories; however, the revision was much smaller than in the case of corn. In spite of this difference, wheat futures rose almost as fast as corn futures prices and continued to rise after WASDE started to revise the inventory forecasts upwards in November 2010 (figure 16). Also in this case, increasing trading activities in wheat derivatives – see figure 23 - could have strengthened the price boom.

Figure 16: Forecasts of market conditions for wheat and wheat futures price movements



1) Monthly forecasts of market conditions in the marketing harvest year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

Figure 17: Forecasts of market conditions for rice and rice futures price movements



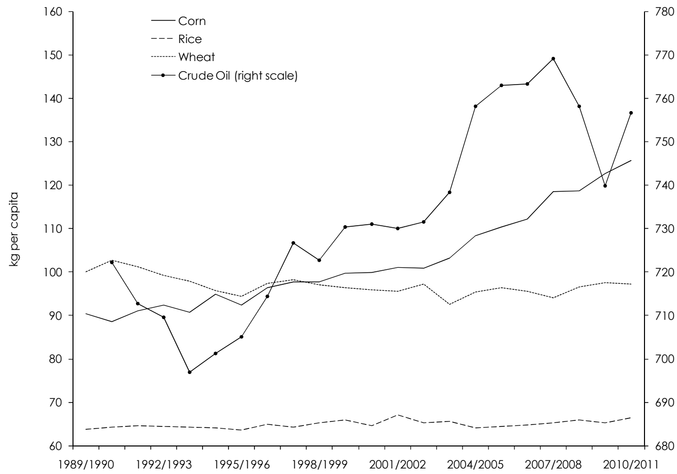
1) Monthly forecasts of market conditions in the marketing harvest year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

In the case of the market for rice, WASDE started to forecast a narrowing of the gap between global production and consumption in October 2007, yet the price boom accelerated and kept going until April 2008 (figure 17). Also the increase of the rice futures price between mid-2010 and mid-2011 by roughly 70% cannot be explained by changes in expectations concerning supply and demand in the spot market as the WASDE did not forecast any significant change in rice inventories over this period (figure 17). At the same time, trading volume in the futures market quadrupled (figure 24). This suggests that speculative activities contributed also to the second price boom 2010/2011.

The presumption that commodity prices did overshoot their fundamental equilibrium (at least) during the last phase of the boom 2007/2008 is confirmed by the extent of the subsequent decline of commodities prices. As regards the futures prices under investigation in this study, crude oil prices fell by 76.0% from their peak in 2008 (until end-2008), corn prices by 59.2%, wheat prices by 65.8%, and rice prices by 43.8% (until these food prices reached their trough in the first half of 2009 – figures 4 to 7).

It has been often asserted that commodity consumption per capita in the global economy has risen strongly in recent years, in particular in emerging market economies due to high income growth in many of these countries (notably in China and India). This development is said to have contributed considerably to the rise in commodity prices. Figure 18 shows a more differentiated picture. Per capita consumption of wheat and rice has remained stagnant over the past 20 years. Due to the production of ethanol, consumption of corn has risen continuously since the late 1990s, since 2002/2003 at a higher rate. However, there was no significant acceleration in demand over 2007 and 2008 when corn prices boomed.

Figure 18: World consumption of corn, rice, wheat and crude oil per capita



Source: U.S. Department of Agriculture, EIA.

Crude oil consumption per capita rose strongly between 2003 and 2005, probably due to the high growth of the global economy. Afterwards, the increase in crude oil consumption slowed down, e. g., between 2005 and 2008, suggesting that demand has adjusted to some extent to the higher price level (also thanks to the rise in the supply of bio-fuels which was an indirect effect of the oil price rise). Between 2008 and 2010, the "great recession" caused demand for crude oil to decline significantly (figure 18).

The empirical evidence presented so far in the figures 4 to 18 suggest that the change in the supply and demand conditions in the markets for physical crude oil, corn wheat and rice cannot fully account for the extent of the wide fluctuations of these commodity prices in recent years. Therefore, the "Bull-bear-hypothesis" might provide a better explanation.

The "bull-bears-hypothesis" sketches an overall picture of trading behaviour and price dynamics in asset markets. Hence, it cannot be directly tested. However, the overall hypothesis contains several clear statements which can be empirically evaluated:

- Market fundamentals alone do not account for the observed price movements (as has been shown in this chapter).
- The use of speculation systems based on trend-following models of technical analysis contribute to the rise in trading activities, in particular, because these systems are using high frequency price data.
- The profitability of technical trading systems is sufficiently high to cause market participants to use these techniques in practice.
- The use of different trend-following trading systems in asset and commodity markets feeds back upon price dynamics, i.e., the aggregate trading signals strengthen and lengthen price trends.

Even though it is not possible to strictly prove the empirical validity of these statements, one can provide some empirical evidence concerning each of these points. If the respective observations are in line with the single statements and, hence, fit together, then the overall empirical picture should be taken as support of the "bull-bear-hypothesis".

In the following chapters I shall first document the dynamics of trading activities in commodity derivatives markets in recent years. I will then analyze the performance of technical trading systems in these markets as well as the price effects of the use of those models.

8. Trading activity in commodity derivatives markets

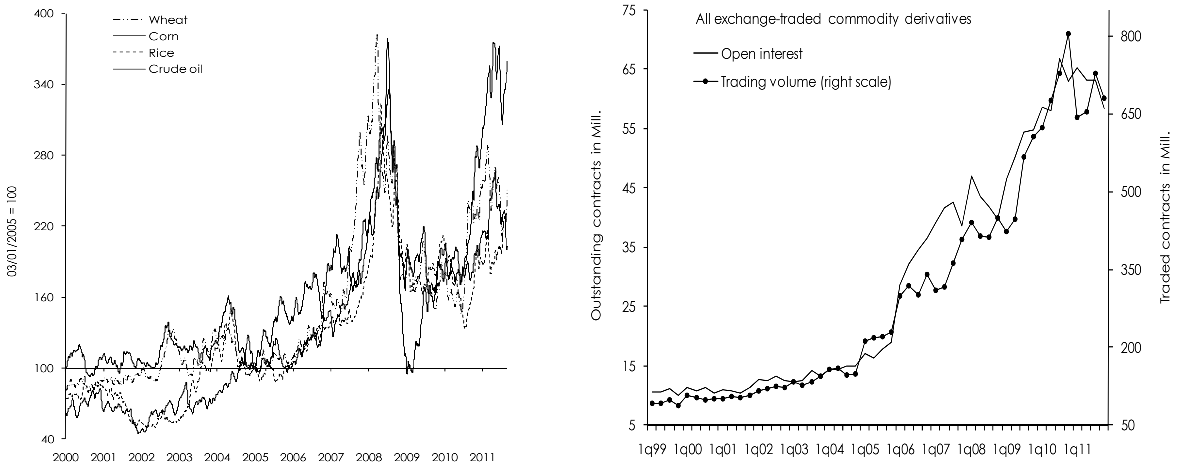
According to the Bank of International Settlements (BIS), trading volume of commodity derivatives contracts rose only moderately between 2000 and 2005, but quadrupled since then (figure 19). The boom in trading activities was particularly strong between the 2nd quarter of 2007 and the 1st quarter of 2008. The second commodity price boom which took off in early 2009 as regards crude oil and in mid-2010 as regards most other commodities was also accompanied by an extremely strong increase in trading activity (figures 1 and 19). The number of outstanding derivatives contracts developed roughly in tandem with trading volume (figure 19).

It does seem rather implausible that a fundamentals-oriented price discovery process should have called for such a strong increase in trading activities in 2007/2008 as well as in 2010.

Hence, this development might rather be related to an increase of (destabilizing) speculation based on a general bullish sentiment (not only in commodity markets but also in stock markets) and carried out by the use of technical trading systems.

This presumption gets support from the fact that commodity futures prices rose dramatically over these two periods, an increase which can hardly be explained by demand and supply conditions in commodity spot markets (as has been demonstrated above). Also the continuous deterioration of the general outlook for the global economy since mid-2007 and since mid-2011, respectively, would have let one to expect a dampening of the commodity price booms rather than its acceleration.

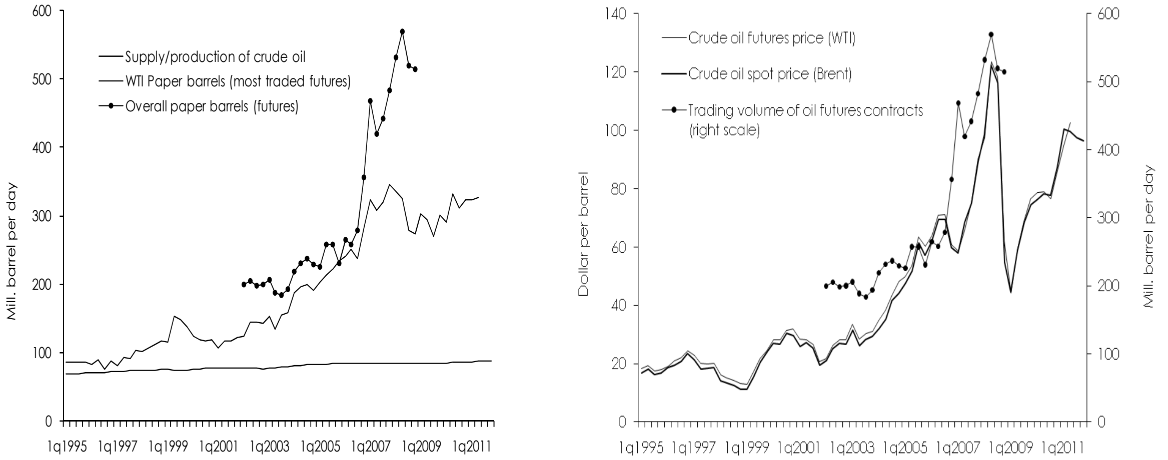
Figure 19: Dynamics of commodity futures prices and derivatives trading activities



Source: New York Mercantile Exchange (NYMEX), Chicago Board of Trade (CBOT), BIZ.

The picture is similar for the single commodity markets investigated in this study. In oil futures markets, e. g., trading activities were booming like never before during the phase of almost "exploding" oil prices (figure 20). By the end of 2008, the daily trading volume of WTI oil futures ("paper barrels") on the two most important US exchanges (NYMEX and ICE) was almost seven times higher than the global production of physical oil (note, that the trading volume of "paper barrels" shown in figure 20 excludes exchange-traded oil options, trading volume on other oil derivatives exchanges like ICE/London or the Dubai Mercantile Exchange as well as all OTC oil derivatives). Even trading volume of just one oil futures contract, the near-by contract on the New York Mercantile exchange, is by a factor of four greater than overall world production of crude oil (figures 20 and 21).

Figure 20: World market for crude oil, oil futures trading and oil price movements

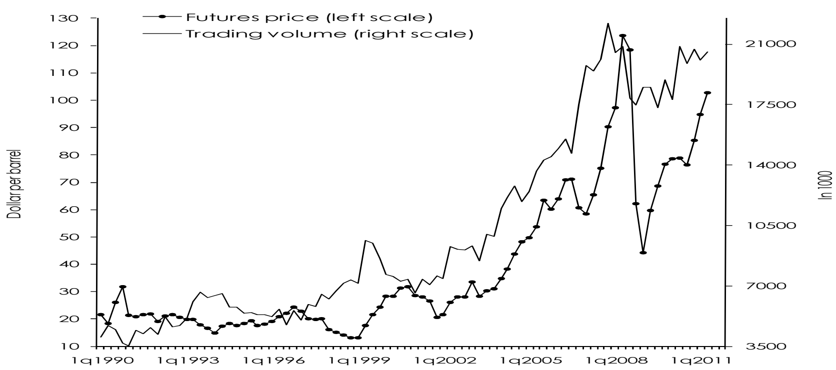


Source: Energy Information Agency (EIA), OECD, New York Mercantile Exchange (NYMEX), Intercontinental Exchange (ICE).

Also the futures markets for corn, wheat and rice experienced a tremendous rise in trading activities since the mid-2000s, in particular before and during the two price booms 2007/2008 and 20010/2011 (figures 22 to 24). Even though the relationship between price movements and trading volume is less pronounced in the case of corn, wheat and rice futures as compared to oil futures, it does seem plausible that destabilizing speculation might has contributed to this coincidence.

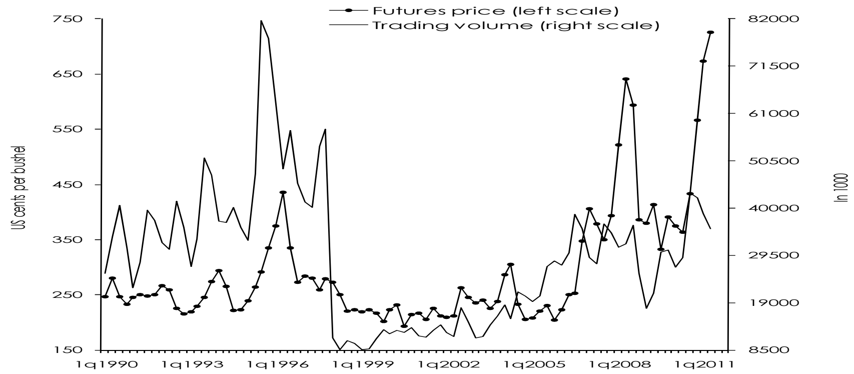
Since trend-following trading strategies based on technical analysis represent the most popular trading technique in asset markets, it seems plausible that the use of these trading systems had significantly contributed to the rise in transaction volume as well as to the price boom in commodity futures markets. Hence, the profitability and the price effects of technical commodity futures trading shall be investigated in the following two sections.

Figure 21: Dynamics of oil futures prices and trading activity 1)



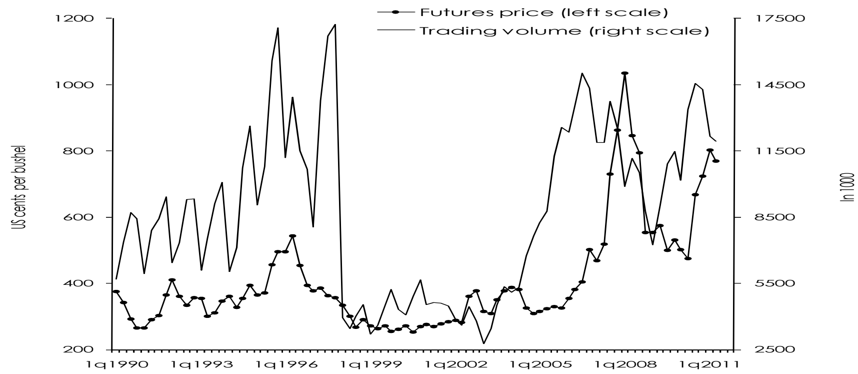
1) Most traded WTI futures contract (NYMEX)

Figure 22: Dynamics of corn futures prices and trading activity 1)



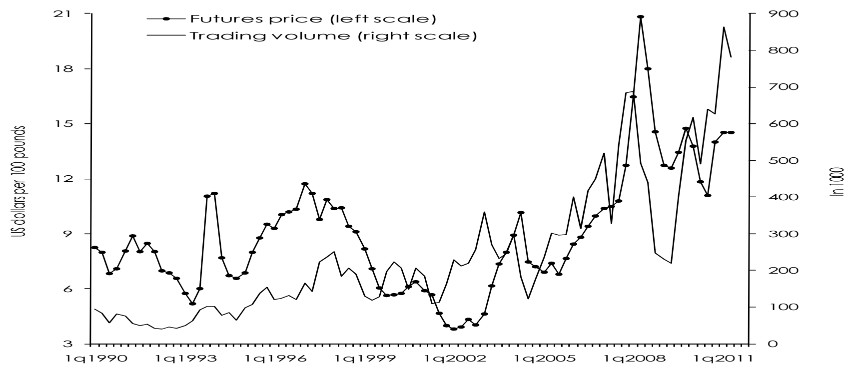
1) Most traded corn futures contract (CBOT)

Figure 23: Dynamics of wheat futures prices and trading activity



1) Most traded wheat futures contract (CBOT)

Figure 24: Dynamics of rice futures prices and trading activity



1) Most traded rough rice futures contract (CBOT)

9. The role of technical analysis in asset trading

In this chapter I shall shortly deal with the popularity of technical trading in modern asset markets and will sketch the basic principles of technical trading systems

9.1 Popularity of technical trading systems

According to survey studies technical analysis is the most widely used trading technique in foreign exchange markets. Over the 1990s the importance of technical analysis has stronger increased than other trading practices like the orientation on fundamentals or on customer orders. Nowadays between 30% and 40% of professional currency traders use technical systems as their most important trading technique (for recent survey studies see *Cheung-Chinn-Marsh*, 2004; *Cheung-Wong*, 2000; *Cheung-Chinn*, 2001; *Oberlechner*, 2001; *Gehrig-Menkhoff*; 2004, 2005A and 2005B; *Menkhoff – Taylor*, 2007).

It is highly probable that technical analysis plays a similar role in other asset markets, particularly in short-term futures trading. This presumption is confirmed by the omnipresence of technical charts on the traders' screens, irrespective of whether futures on stock indices, bonds or commodities are traded (for a documentation of the popularity of technical analysis in futures markets see *Irwin-Holt*, 2004).

Since technical trading systems are so widely used in financial markets they are continuously monitored even by those traders who do not believe in technical analysis. By observing the transactions and open positions indicated by the most popular technical systems a trader can draw conclusions about the behaviour of other actors and their potential price effects. To put it differently: Monitoring technical models helps the trader to deal with Keynes' "beauty contest" problem, i.e., how to form expectations about other traders' expectations.

9.2 How technical trading systems work

Technical analysis tries to exploit price trends which "technicians" consider the most typical feature of asset price dynamics ("the trend is your friend"). Hence, this trading technique derives buy and sell signals from the pattern of the most recent price movements which (purportedly) indicate the continuation of a trend or its reversal (trend-following or contrarian models). Technical traders believe that the phenomenon of trending occurs across different time scales, hence, they apply their models to different data frequencies (for an introduction into technical analysis see *Neely*, 1997; for a comprehensive treatment see *Kaufman*, 1987; *Murphy*, 1986).

Two different approaches have been developed for isolating upward and downward price trends from oscillations around a stable level, called "whipsaws" in the traders' jargon.

The qualitative approaches rely on the interpretation of some (purportedly) typical configurations of the ups and downs of price movements like "head and shoulders" or "top and bottom" formations. The chartist trading techniques contain therefore an important subjective element (note, however, that appropriate computer software can provide the basis for a more objective identification of chart configurations – see *Chang-Osler*, 1999; *Osler*, 2000; *Lo-Mamaysky-Wang,* 2000). The quantitative approaches try to identify trends using statistical transformations of past prices. These models produce clearly defined buy and sell signals which can be tested accurately.

Since one cannot know precisely which models are actually used in practice, one should restrict an analysis of the performance of technical analysis to the most popular and most simple types of models. A review of the literature on technical analysis as well a survey of technical trading software reveals that moving average models and momentum models meet both criteria.

The basic version of the first type of model consists of a (unweighted) short-term moving average (MAS) and a long-term moving average (MAL) of past prices. The length of MAS usually varies between 1 day (in this case the original price series serves as the shortest possible MAS) and 10 days, that of MAL between 20 and 50 days.

The trading rule of the basic version of moving average models is as follows:

Buy (go long) when the short-term (faster) moving average crosses the long-term (slower) moving average from below and sell (go short) when the converse occurs. Or equivalently: Hold a long position when the difference MAS-MAL is positive, otherwise hold a short position.

The second type of model works with the difference between the current price and that i days ago:

$M(i) = P_t - P_{t-i}$

The trading rule of the basic version of momentum models is as follows:

Buy (go long) when the momentum M(i) turns from negative into positive and sell (go short) in the opposite case. Or equivalently: Hold a long position when M(i) is positive, otherwise hold a short position.

Since the variables (MAS-MAL) or M(i) fluctuate around zero, they are often called "oscillators" (figures 25 to 28 show how a MA model and a momentum model would have performed in the oil, corn, wheat and rice futures markets).

Price oscillations often cause technical models to produce "wrong" signals. In order to filter them out the signal execution can be delayed by n days, i.e., a signal is executed only if it remains valid over n consecutive days. In this study only the shortest possible lag of signal execution is tested (1 day).

There exist many modifications of moving average and momentum models (see, e.g., *Kaufman*, 1987, chapters 5 and 6). However, in order to prevent the suspicion of "model mining" and to keep the analysis simple, this study considers only the basic version of moving average and momentum models.

The present study analyzes the interaction between the dynamics of commodity futures prices and technical trading on the basis of daily data, not least for reasons of keeping the investigation simple. However, one has to keep in mind that most technical futures trading is nowadays done on an intraday basis and, hence, uses high frequency data (ranging from tick data to hourly data). Therefore, it is assumed that the medium-term and long-term price trends are primarily brought about through net long (short) overnight positions and much less by the sequences of intraday trends.

10. Performance of technical trading systems in commodity futures markets

In this chapter I document the performance of a great number of technical trading systems in the commodity futures markets of crude oil (NYMEX) as well as of corn, wheat and (rough) rice (CBOT).

10.1 Selection of the models under investigation

The analysis of the interaction between technical trading and price movements in commodity futures markets comprise 1092 technical models. In the case of moving average models all combinations of a short-term moving average (MAS) between 1 and 15 days and a long-term moving average (MAL) between 20 and 60 days are tested under the restriction that the lengths of MAL and MAS differ by at least 20 days (495 models). In the case of momentum models the time span i runs from 10 to 60 days (51 models). Each model is simulated with and without a lag of signal execution by one day (delay filter). Hence, a total of 1092 different technical trading models are analyzed (990 MA-models and 102 momentum models).[12])

The sample comprises a wide range of different technical models. The "fastest" models (i. e., those with a comparatively short length of MAS and MAL in the case of MA models and with a short time span M in the case of momentum models, respectively) produce roughly 30 trading signals per year. Hence, the open positions generated by these models last only 12 days on average. The "slowest" models like the MA model 15/60 (MAS=15, MAL=60) or the

[12]) A similar set of technical models was used when testing the profitability and the price effects of technical currency trading (*Schulmeister*, 2006; 2008A; 2009B; 2009C). However, due to the higher volatility of commodity futures prices as compared to exchange rates, the length of MAL of the models under investigation in the present study (between 20 and 60 days) is longer than in the exchange rate studies (between 5 and 40 days). Also the time span M of momentum models is wider (between 10 and 60 days) when testing technical trading in commodity futures markets as compared to foreign exchange markets (between 5 and 40 days). The length of MAS (between 1 and 15 days) is the same in both studies. The overall number of technical models tested in this study (1092) is only slightly higher than in the case of the exchange rate studies (1024).

momentum model 60 (time span M=60) produce only 5 trading signals per year, their open positions last almost 75 days on average.

This approach differs from the usual procedure of testing the profitability of trading rules. In most studies, this is done in the following way. The researcher selects out of a sample of some hundreds or even thousands different rules the best performing one and then tests for the statistical significance of their profitability. This is done using the "bootstrap" methodology (see, e. g., *Brock – Lakonishok - LeBaron*, 1992; *Levich - Thomas*, 1993) and in addition the "reality check for data snooping" (see, e. g., *Sullivan – Timmermann - White*, 1999; Park-Irwin, 2005; *Neely – Weller – Ulrich*, 2007; *Marshall – Cahan – Cahan*, 2008). In most cases it then turns out that the ex-post best performing models do not survive these tests. The reason is simple: Their ex-post-profitability is mainly due to "data snooping" or "model mining" and, hence, is achieved just by chance.

To put it differently: Since the researcher restricts the analysis of the performance of trading systems to only a few ex-post best performing models he himself practices a "biased selection" which he then "detects" by testing for a "data snooping bias". From this result it is then concluded that technical trading in general is not consistently profitable. Such a conclusion is not warranted because in practice (experienced) technical traders do not use such a (necessarily biased) optimization procedure. By contrast, the literature for practitioners warns against (over)optimization precisely because this causes one to select a model out of the extreme right tail of a probability distribution of a great number of models. In particular it is warned against the use of a very great number of "test models" since the probability of committing a "selection error" increases with the number of "test models". For these reasons practitioners restrict their selection to a range of models which have performed relatively stable over the long run (the literature often concretizes the parameter ranges for a specific market) instead of choosing a model which performed best over a recent (and arbitrarily specified) "test period".

The present study documents therefore the performance of the total sample of 1092 technical models which are selected according to a certain range of the model parameters. Due to the generally defined selection criteria which are used for all four commodity futures markets, many of the models under investigation produce substantial losses (as shall later be documented). In addition, the procedure of analyzing technical trading systems applied in the present study was already used in studies on the performance and price effects of trading systems in the foreign exchange market as well as in the stock market (*Schulmeister*, 2006, 2008A, 2009B, 2009C). For these reasons the results of these studies as well as of the present study can hardly be attributed to "data snooping".

10.2 Assumptions underlying the simulations

The simulation of technical commodity futures trading is based on the following assumptions. It is assumed that the most liquid contract is traded. An inspection of trading volume by contract maturities reveals this is the near-by contract until (roughly) the 10th day of the expiration month. Hence, it is assumed that the technical trader rolls over his open position on that day (or the next following business day) from the near-by contract to the contact which is to expire next. [13])

In order to avoid a break in the signal generating price series, the price of the contract which is next to expire after the near-by contract is indexed with the price of the near-by contract as a base (software for technical trading in the futures markets also provide such "price shifts at contract switch"). This "synthetic" price series is, however, only used for the generation of trading signals, the execution of the signals is simulated on the basis of the actually observed prices.

When simulating the performance the trading systems, the open price is used for both the generation of trading signals as well as for the calculation of the returns from each position. Using open prices ensures that the price at which a trade is executed is very close to that price which triggered off the respective trading signal (this would not be the case if one used the daily close price).

Transaction costs are estimated under the assumption that the technical models are used by a professional trader on electronic exchanges. In the crude oil futures markets, e. g., one pays nowadays (much) less than 10$ for a round trip. This implies commissions of less than .005% of contract value (at an oil futures price of 100$). Hence the simulation of technical commodity futures trading operates under the assumption of overall transaction costs of 0.01% (per trade).[14])

The profitability of the trading systems is calculated in the following way. The single rate of return (SRR_i) from any position i opened at time t and closed at t+n is

$SRR_i = \{(P_{t+n} - P_t)/P_t\} * 100$ for long positions (P_{t+n} is the sell price)

$SRR_i = \{(P_t - P_{t+n})/ P_t\} * 100$ for short positions (P_t is the sell price)

The single rates of return can be considered as absolute returns in cents if one assumes that there is always 1$ in the game (value of any open position). The sum of all positive (negative) returns gives the gross profits (losses). The gross rate of return (per year) is then the difference between gross profits (per year) and gross losses (per year). If one subtracts transaction costs

[13]) The only exception concerns trading in the CBOT corn futures market between June and August. Over this period, the trading volume of the December contract is usually higher than that of the September contract. Hence, it is assumed that the technical trader switches on June 10th his position from the July contract to the December contract.

[14]) Since the contract value in the corn, wheat and rice futures markets is significantly lower than in the crude oil futures market, transaction costs (as percentage of contract value) are somewhat higher when trading corn, wheat or rice futures as compared to oil futures. The same is true for futures trading in the more distant past (when electronic exchanges did not exist yet). However, in order to keep the results comparable across markets and time periods the calculations operate with the assumption of transaction costs of .01% of contract value in all cases (the same assumption is made in a study on S&P 500 futures trading - *Schulmeister*, 2009C).

one gets the net rate of return (the number of transactions is always twice the number of open positions and, hence, of the single returns).

The gross rate of return (GRR) of any technical trading model can be split into six components, the number of profitable/unprofitable positions (NPP/NPL), the average return per day during profitable/unprofitable positions (DRP/DRL), and the average duration of profitable/unprofitable positions (DPP/DPL). The following relationship holds:[15])

GRR = NPP*DRP*DPP – NPL*DRL*DPL

The probability of making an overall loss when blindly following a technical trading model is estimated by testing the mean of the single rates of return against zero (only if it is negative does the trading rule produce an overall loss).[16])

10.3 How single models perform during the bull-bear-years 2007 and 2008

Figure 25 and table 2a demonstrate how a (slow) moving average model (MAS=15, MAL=60) and a (slow) momentum model (time span i = 60) perform in the WTI oil futures market between January 3, 2007 and December 30, 2008. First, I shall show how these models profit from persistent price trends. Over the months of June and July 2007, the MAS is higher than the MAL (the MA oscillator is positive as is the momentum oscillator – figure 25), hence, the MA model holds a long position (as does the momentum model). This position is rolled over to the second nearest (September) contract on July 10, i.e., the August contract is sold and the September contract is bought at a price of 70.40 per (paper) barrel (table 1a – "n" means that the model goes neutral, i.e., it sells if it closes a long position and it buys if it closes a short position). At that time, the (cumulative) rate of return per year since the beginning of the trading period is negative (-10.49%).

On August, 27, 2007, the MA model switches from long to short. On September 7, the position is reversed at a single loss of 7.56% (or 7.56 cents if one "normalizes" the value of the open position to 1 $). Due to a strong and persistent "underlying" upward trend, this long position is held until January 25, 2008 when it is closed at a profit of 23.24 cents (the sum of all single profits and losses realized at contract switches between September 7, 2007 and January 25, 2008 – table 2a).

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[15]) When calculating these components, all those transactions are neglected which are only caused by switching futures contracts (these transactions are, however, taken into account when calculating the net rate of return). E. g., if a model opens a long position in the crude oil futures market on March 2 (and, hence in the April contract), switches to the May contract on March 10, and closes the position on March 22, then DPP is calculated as 20 days.

[16]) The t-statistic of the means of the single returns measures their statistical significance and, hence, estimates the probability of making an overall loss when following a specific trading rule. The t-statistic is therefore conceptually different from the Sharpe ratio which measures the univariate risk-return relation. As the number of observations goes to infinity, an estimated t-statistic will go to zero or to positive or negative infinity. By contrast, an estimated Sharpe ratio will converge to the true Sharpe ratio. However, in the context of the present study (with finite samples) the informational content of the t-statistic and the Sharpe ratio is equivalent. This is so because the t-statistic differs from the Sharpe ratio only by the factor $\sqrt{n-1}$ (where n is the sample size) and by the risk-free rate.

Figure 25: Technical trading signals for WTI crude oil futures 2007 – 2008

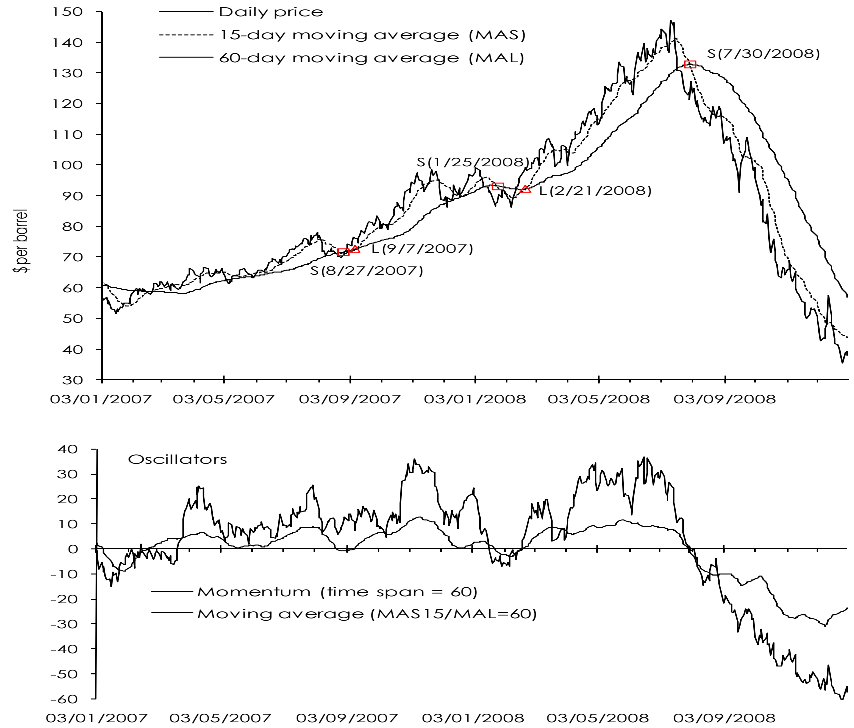


Figure 26: Technical trading signals for corn futures 2007 – 2008

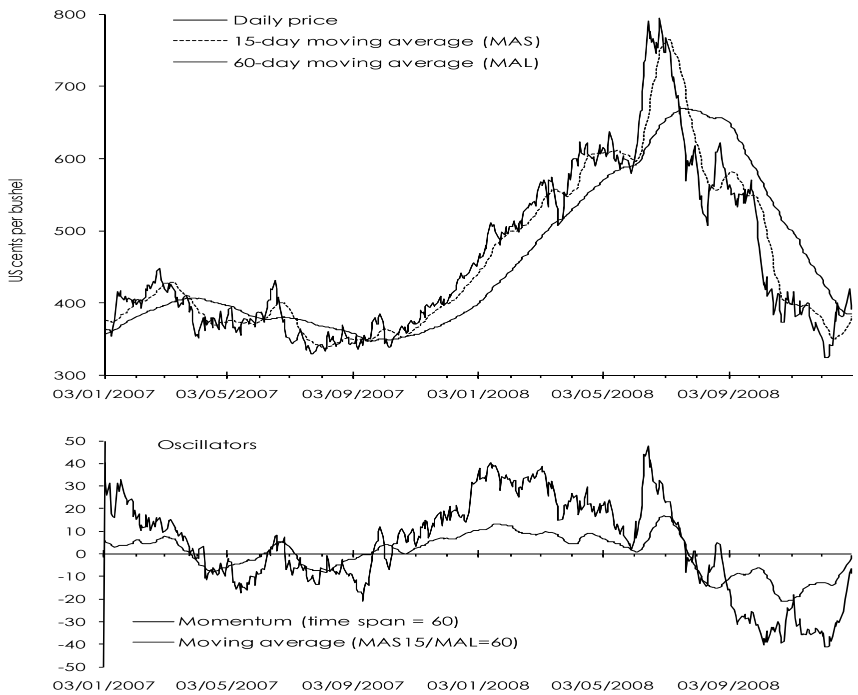


Figure 27: Technical trading signals for wheat futures 2007 – 2008

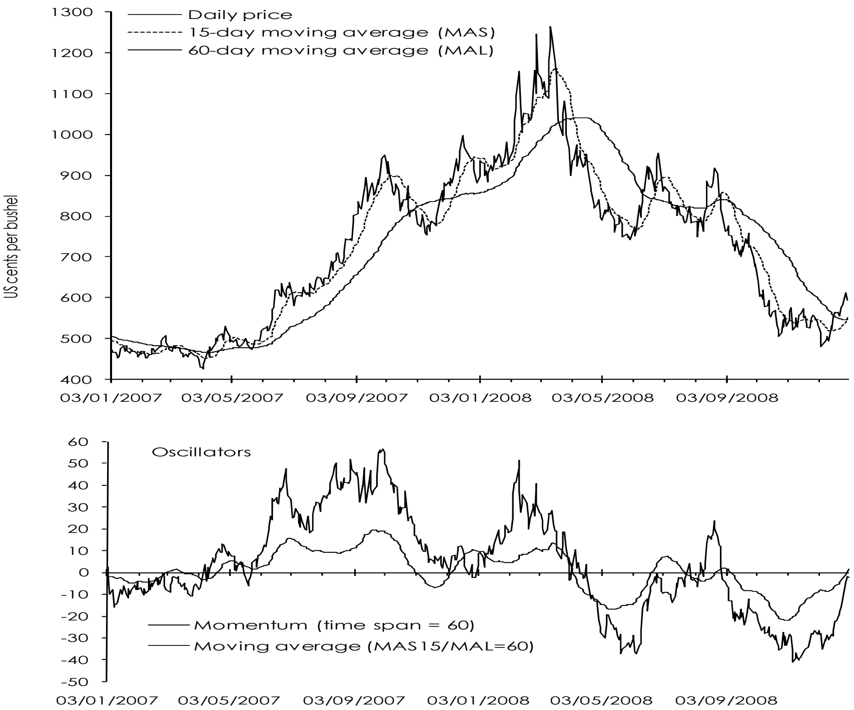
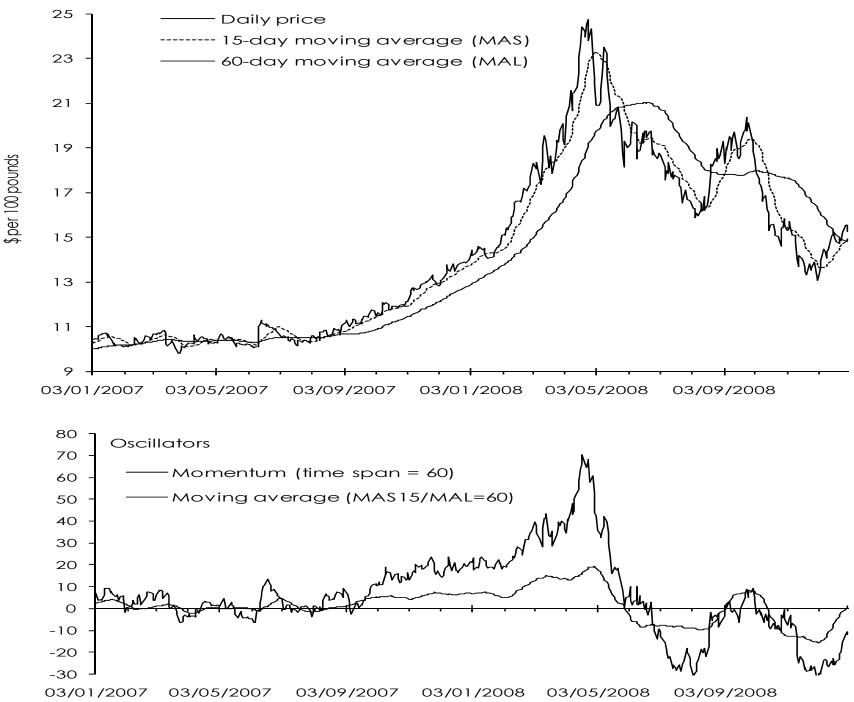


Figure 28: Technical trading signals for rice futures contract 2007 – 2008



The last open position "rides" an even steeper upward trend of oil prices (figure 25), it produces an overall profit of 23.77 cents between February 21, and July 30 (as the bull market sharply tilted into a bear market the last transaction is highly unprofitable). The downward trend is fully exploited by the model (it sells at 121.4 $ and buys back at 39.20 $), producing an even higher return than the preceding upward trend (during bear markets prices mostly change faster than during bull markets, e. g., persistent downward trends are steeper than upward trends – figure 25).

Over the entire trading period, the MA model 15/60 would have achieved a (unleveraged) gross rate of return per year (GRR) of 65.64% per year. At margin rates of roughly 6%, the leveraged rate of return in oil futures trading (relative to the margins "invested") is almost 17 times higher than the unleveraged rates.

Figure 25 also provides some evidence about the "speed" at which technical models with different parameters and, hence, with a different sensitivity to price movements, get on a trend. The crossing points between the daily price and the 15-days-MA represent trading signals of a relatively "fast" model (MA model 1/15). As regards the last upward trend, e. g., the MA model 1/15 opens a long position already 10 days earlier than the relatively "slow" MA model 15/60. Over these 10 days technical models gradually change their position from short to long, the "fast" models at first, the "slow" models at last. The execution of the resulting sequence of buy signals then contributes to the strength of the trend (this feed-back shall later be investigated).

As all important commodity markets experienced a bull market between early 2007 and mid-2008, followed by a general bear market, the MA model 15/60 would have been profitable also in trading of corn futures (GRR: 34.94%) and wheat futures (GRR: 30.69%). Only trading of rough rice futures would have been slightly unprofitable (GRR: -1.46%), mainly because of the low "speed" of the MA model and the fact that a particularly strong counter-movement took place during the bear market of 2008 (figure 28).

Figures 26 to 28, and tables 2b to 2d, in the annex document the performance of this MA model in these three futures markets over 2007 and 2008.

Table 2a: Performance of 1092 technical trading systems in the oil futures market

Price series: Daily prices of the WTI crude oil futures contract
Begin of trading: 01/03/2007
End of trading: 12/30/2008

Short-term moving average (MAS): 15
Long-term moving average (MAL): 60

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
07/10/2007	l	0	72.7	0.00	-6.61
08/10/2007	n	31	70.6	-2.89	-10.49
08/10/2007	l	0	70.4	0.00	-10.49
08/27/2007	s	17	70.8	0.57	-8.86
09/07/2007	l	11	76.2	-7.56	-19.63
09/10/2007	n	3	75.9	-0.39	-19.97
09/10/2007	l	0	74.7	0.00	-19.97
10/10/2007	n	30	80.4	7.56	-7.97
10/10/2007	l	0	79.7	0.00	-7.97
11/12/2007	n	33	94.7	18.83	14.83
11/12/2007	l	0	93.6	0.00	14.83
12/10/2007	n	28	88.7	-5.24	8.01
12/10/2007	l	0	88.8	0.00	8.01
01/10/2008	n	31	94.2	6.14	13.37
01/10/2008	l	0	93.8	0.00	13.37
01/25/2008	s	15	90.4	-3.66	9.40
02/11/2008	n	17	91.9	-1.66	7.50
02/11/2008	s	0	91.9	0.00	7.50
02/21/2008	l	10	99.1	-7.89	0.36
03/10/2008	n	18	104.8	5.75	5.21
03/10/2008	l	0	103.8	0.00	5.21
04/10/2008	n	31	110.8	6.70	10.14
04/10/2008	l	0	110.0	0.00	10.14
05/12/2008	n	32	124.5	13.23	19.24
05/12/2008	l	0	124.9	0.00	19.24
06/10/2008	n	29	136.8	9.53	24.81
06/10/2008	l	0	136.5	0.00	24.81
07/10/2008	n	30	136.7	0.14	23.56
07/10/2008	l	0	137.3	0.00	23.56
07/30/2008	s	20	121.4	-11.58	15.37
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
12/30/2008	n	20	39.2	16.17	65.64

10.4 Performance of technical commodity trading 1989 - 2011

Tables 3a and 4a show the performance of six moving average and six momentum models over the entire sample period January 2nd, 1989, to June 30, 2011 (the analogous tables 3b to 3d, and 4b to 4d for corn, wheat and rice futures trading are to be found in the annex). The fastest model is a momentum model with a time span of 10 days when trading oil futures. This model displays an average duration of profitable positions (DPP) of only 19.8 days, and, hence, focuses on (very) short-term trends. Most other selected models produce much longer DPPs, up to 147.1 days in the case of the MA model 15/60 trading rice futures.

Table 3a: Pattern of trading the WTI crude oil futures contract 1989 to 2011 (June)

	Moving average models					
Length i of MAS	1	1	5	10	15	15
Length i of MAL	30	30	35	40	45	60
Lag of signal execution		1				
Gross rate of return per year	15.27	12.37	9.93	9.39	10.74	10.42
Sum of profits per year	51.12	43.16	39.59	36.87	35.08	32.73
Profitable positions						
Number per year	5.16	4.22	3.47	2.84	2.76	1.91
Average return						
Per position	9.92	10.22	11.42	12.96	12.73	17.13
Per day	0.199	0.171	0.162	0.154	0.136	0.132
Average duration in days	49.84	59.65	70.56	84.28	93.58	129.65
Sum of losses per year	-35.84	-30.79	-29.65	-27.48	-24.34	-22.31
Unprofitable positions						
Number per year	14.49	7.78	6.22	4.53	3.47	2.98
Average return						
Per position	-2.47	-3.96	-4.77	-6.06	-7.02	-7.49
Per day	-0.332	-0.272	-0.246	-0.219	-0.227	-0.190
Average duration in days	7.46	14.55	19.35	27.64	30.91	39.37
Distribution of the single rates of return						
Mean	0.778	1.031	1.025	1.273	1.726	2.131
t-statistic	1.797	1.569	1.177	1.104	1.362	1.276
Median	-1.400	-1.484	-1.770	-2.720	-1.704	-3.095
Standard deviation	9.086	10.775	12.838	14.814	14.939	17.433
Skewness	5.490	3.913	4.363	3.899	2.995	2.578
Excess kurtosis	47.226	25.664	32.930	23.691	15.569	9.606
Sample size	442	270	218	166	140	110

Based on a cluster analysis of all 1092 models, three classes of models are distinguished according to the average lengths of profitable positions: Short-term models (comparatively "fast" models) produce an average durations of profitable positions (DPP) up to 60 days, medium-term models are those with an average DPP between 60 and 100 days, long-term ("slow") produce an average DPP longer than 100 days. Tables 3 and 4 show that the length of DPP depends on the parameters of the model: The longer are MAS and MAL, and the greater is the time span M, the longer is DPP of MA models, and of momentum models, respectively. Models with a lag of signal execution of 1 day produce much longer DPPs as compared to the same model without this delay filter.

Almost all of the 48 selected models are profitable, only three of them produce small losses (tables 3 and 4).

Table 4a: Pattern of trading the WTI crude oil futures contract 1989 to 2008 (June)

Momentum models

Time span i	10	1	35	35	60	60
Lag of signal execution		10		1		1
Gross rate of return per year	-0.63	3.32	6.93	5.97	15.53	17.24
Sum of profits per year	59.35	50.95	41.38	37.37	40.24	37.60
Profitable positions						
Number per year	12.09	7.33	6.13	3.51	4.27	2.49
Average return						
Per position	4.91	6.95	6.75	10.64	9.43	-4.16
Per day	0.255	0.211	0.163	0.154	0.156	-0.191
Average duration in days	19.25	32.99	41.46	69.18	60.57	21.84
Sum of losses per year	-59.98	-47.62	-34.45	-31.40	-24.71	-20.35
Unprofitable positions						
Number per year	22.31	11.33	11.55	6.53	8.27	4.89
Average return						
Per position	-2.69	-4.20	-2.98	-4.81	-2.99	-4.16
Per day	-0.453	-0.387	-0.311	-0.257	-0.232	-0.191
Average duration in days	5.93	10.86	9.58	18.69	12.89	21.84
Distribution of the single rates of return						
Mean	-0.018	0.178	0.392	0.594	1.239	2.337
t-statistic	-0.091	0.462	0.869	0.732	1.648	1.847
Median	-0.979	-1.327	-1.110	-1.949	-1.081	-1.442
Standard deviation	5.559	7.889	8.985	12.171	12.601	16.255
Skewness	2.552	2.174	5.766	4.098	4.812	3.637
Excess kurtosis	13.508	10.842	53.827	28.541	28.163	16.064
Sample size	774	420	398	226	282	166

The gross rate of return (GRR) of any technical trading model can be split into six components, the number of profitable/unprofitable positions (NPP/NPL), the average return per day during profitable/unprofitable positions (DRP/DRL), and the average duration of profitable/unprofitable positions (DPP/DPL). The following relationship holds:

GRR = NPP*DRP*DPP – NPL*DRL*DPL

The selected models have the following trading pattern in common (tables 3 to 6):

- The number of unprofitable trades is (much) higher than the number of profitable trades; the fastest MA models produce even more than three times as many single losses than single profits.
- The average return per day during profitable positions is significantly smaller (in absolute terms) than during unprofitable positions.
- Profitable positions last on average 3 to 6 times longer than unprofitable positions.

The overall profitability of the models is therefore due to the exploitation of persistent commodity price trends. Short price fluctuations often cause technical models to produce losses, which, however, are comparatively small, because the hold unprofitable positions for a short period of time (as compared to profitable positions).

The distribution of the single rates of return reflects these properties of technical trading systems:

- The median is negative.
- The standard deviation is several times higher than the mean.
- The distribution is skewed to the right and leptokurtotic.

The probability of making an overall loss by blindly following a technical trading model is estimated by testing the mean of the single rates of return against zero (only if it is negative does the trading rule produce an overall loss). The t-statistic of only 3 of the 12 selected models trading oil futures (tables 3a and 4a) exceeds 1.645. Hence, only for a quarter of the models was the probability of making an overall loss smaller than 1%. The t-statistics are much lower when the same models trade corn and wheat futures (table 3b, 3c, 4b, 4c). In the case of trading rice futures do the models produce the highest t-statistics on average (tables 3d and 4d).

Table 5 classifies all models according to their performance as measured by the t-statistic into three groups and quantifies the components of profitability for each of them. When trading in the crude oil futures market, only 1.8% of all models achieve a t-statistic greater than 2 and the average (gross) rate of return per year over these modes amounts to 18.2%. The t-statistic of 83.0% of all models lies between 1.0 and 2.0 (average rate of return: 11.3%), 15.2% generate a t-statistic smaller than 1.0 (average rate of return: 7.1%). The average annual gross rate of return (GRR) over all 1092 models is 10.8%.

The performance of technical trading systems in the corn and wheat futures markets is less profitable as compared to oil futures trading, the annual GRR amounts to only 3.7% and 1.8%, respectively. Hence, no model produces a t-statistic greater 2. The same technical models perform much better in rice futures trading, their annual GRR amounts to 11.3%, 14.9% of the models achieve a t-statistic greater than 2 (table 5).

The pattern of profitability is the same for each class of models as well as for all four futures markets. The number of unprofitable positions (single losses) exceeds the number of profitable positions (single profits), the average return per day is higher during unprofitable positions than during profitable positions, so that the overall profitability is exclusively due to the profitable positions lasting three to five times longer than the unprofitable positions.

Table 5: Components of the profitability of 1092 trading systems by types of models

Moving average and momentum models, daily data, 1989 to 2011 (June)

	Number of models				Mean over each class of model					
	Abolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number per year	Return per day	Duration in days	Number per year	Return per day	Duration in days
					WTI crude oil futures contract					
t-statistic of the mean of the single returns										
< 1.0	166	15.2	7.08	0.839	3.62	0.161	73.29	8.25	-0.276	16.98
1.0 - <=2.0	906	83.0	11.30	1.358	3.08	0.155	86.62	5.41	-0.230	25.10
> 2.0	20	1.8	18.23	2.219	5.79	0.183	51.97	10.21	-0.293	11.28
All models	1092	100.0	10.79	1.295	3.22	0.156	83.96	5.93	-0.238	23.61
Moving average models	990	90.7	10.60	1.276	3.01	0.155	86.53	5.62	-0.233	24.59
Momentum models	102	9.3	12.57	1.473	5.16	0.170	58.99	8.95	-0.286	14.16
Models with lag = 0	546	50.0	10.94	1.315	3.44	0.158	81.22	6.74	-0.250	21.65
Models with lag = 1	546	50.0	10.63	1.275	2.99	0.154	86.69	5.13	-0.227	25.57
					Corn futures contract					
t-statistic of the mean of the single returns										
< 1.0	850	77.8	2.69	0.466	3.15	0.117	82.93	7.12	-0.197	21.28
1.0 - <=2.0	242	22.2	7.40	1.272	2.50	0.106	108.17	4.86	-0.162	28.81
> 2.0	-	-	-	-	-	-	-	-	-	-
All models	1092	100.0	3.73	0.645	3.01	0.115	88.52	6.62	-0.189	22.95
Moving average models	990	90.7	3.67	0.635	2.79	0.114	91.59	6.28	-0.186	23.92
Momentum models	102	9.3	4.37	0.737	5.12	0.124	58.73	9.96	-0.227	13.59
Models with lag = 0	546	50.0	3.62	0.627	3.24	0.116	85.76	7.50	-0.200	20.99
Models with lag = 1	546	50.0	3.84	0.662	2.77	0.114	91.29	5.74	-0.179	24.92
					Wheat futures contract					
t-statistic of the mean of the single returns										
< 1.0	1061	97.2	1.68	0.291	2.92	0.120	84.85	6.74	-0.178	24.99
1.0 - <=2.0	31	2.8	6.65	1.122	4.30	0.143	60.42	9.09	-0.203	15.64
> 2.0	-	-	-	-	-	-	-	-	-	-
All models	1092	100.0	1.82	0.315	2.96	0.121	84.16	6.81	-0.179	24.72
Moving average models	990	90.7	1.92	0.333	2.72	0.120	87.51	6.43	-0.173	25.82
Momentum models	102	9.3	0.86	0.139	5.28	0.128	51.65	10.53	-0.230	14.05
Models with lag = 0	546	50.0	1.84	0.317	3.17	0.123	82.30	7.74	-0.187	22.93
Models with lag = 1	546	50.0	1.80	0.313	2.75	0.118	86.02	5.88	-0.171	26.51
					Rice futures contract					
t-statistic of the mean of the single returns										
< 1.0	16	1.5	5.39	0.813	3.46	0.116	87.37	7.15	-0.205	20.56
1.0 - <=2.0	913	83.6	10.84	1.599	3.08	0.123	92.17	5.90	-0.183	23.24
> 2.0	163	14.9	14.48	2.150	3.30	0.127	86.08	4.89	-0.166	25.92
All models	1092	100.0	11.30	1.670	3.11	0.123	91.19	5.77	-0.181	23.60
Moving average models	990	90.7	11.39	1.677	2.91	0.123	94.38	5.46	-0.177	24.57
Momentum models	102	9.3	10.47	1.597	5.09	0.132	60.24	8.71	-0.214	14.26
Models with lag = 0	546	50.0	11.40	1.690	3.34	0.125	88.10	6.51	-0.189	21.54
Models with lag = 1	546	50.0	11.20	1.650	2.89	0.122	94.28	5.02	-0.172	25.66

This pattern of profitability is characteristic for technical trading in general, it was also found in the case of technical currency trading as well as technical stock trading (*Schulmeister*, 2008A, 2009C). The main difference between technical trading in commodities markets and in currency markets as well as in stock markets concerns the risk of making an overall loss: It is much higher in commodities trading as compared to currency and stock trading (the t-statistics are much lower in the case of the former). The reason for that lies in the higher volatility of daily price changes in commodities market as compared to currency or stock markets.

10.5 Performance of technical models during the bull-bear-years 2007 and 2008

In periods of strong and persistent commodity price trends ("bulls" and "bears"), technical models produce greater profits than on average. Hence, technical speculation becomes more attractive, causing more market participants (in particular hedge funds and investment banks) to use technical models. The execution of the respective trading signals then strengthens and lengthens the trend. To illustrate this interaction, I document how the same 1092 models perform over the recent period of rising commodity prices (January 2007 to June 2008), followed by a period of steeply falling prices.

Between January 2007 and December 2008, the 1092 technical models produce profits which are much higher than over the entire sample period (compare table 6 to table 5). The models achieve a GRR of 66.5% per year on average when trading oil futures markets, 16.4% when trading corn futures, 27.8% when trading wheat futures, and 16.7% when trading rice futures. As leveraged returns are roughly 15 times higher in commodity futures markets than the (unleveraged) gross or net rate of returns displayed in table 6, the profits one could have made through technical commodity speculation were huge. However, one should keep in mind that also the risk was substantial as can be seen from the low t-statistics. This result is mainly due to high price volatility but it is in part also due to the small sample size (in oil futures trading, e. g., the 1092 models produced only roughly 15 open positions over the 24-months-period).

10.6 Profitability of trading systems over sub-periods ex post and ex ante

The study divides the overall sample period of 22.5 years into 6 sub-periods. The years 1989 to 2004 are divided into four periods each lasting 4 years. The years of rising commodity price fluctuations (2005 to 2011) consists of the sub-period covering the great bull market (2005 to June 2008), followed by the period of one bear market and one bull market (June 2008 to June 2011). In this section the performance of the 1092 models over each sub-period is documented, both ex post (in sample) as well as ex ante (out of sample).

The ex-post-performance of all models over the sub-periods in the oil futures market can be summarized as follows (table 7a). First, these models would have made losses in only 1138 out of 6552 cases (1092 models over 6 sub-periods). Second, the average profitability of technical oil futures trading has been declining over the long run. This tendency was only interrupted in the sub-period 2005 to June 2008 due to the strong and long lasting bull market. Between July 2008 and July 2011, the 1092 models produced an average loss when trading oil futures in spite of the pronounced bear market which could be profitably exploited by technical trading (table 6). The main reason for the weak performance of the trading systems lies in the more erratic price movements afterwards, in particular between mid-2009 and mid-2010 (figure 4).

Table 6: Components of the profitability of 1092 trading systems by types of models
Moving average and momentum models, daily data, 2007 to 2008

	Number of models		Mean over each class of model							
	Abolute	Share in %	Gross rate of return	t-statistic	Profitable positions			Unprofitable positions		
					Number per year	Return per day	Duration in days	Number per year	Return per day	Duration in days
					WTI crude oil futures contract					
t-statistic of the mean of the single returns										
< 1.0	317	29.0	57.56	0.925	2.90	0.320	95.24	4.55	-0.027	24.47
1.0 - <=2.0	775	71.0	70.17	1.141	3.16	0.318	94.56	4.93	-0.219	21.52
All models	1092	100.0	66.51	1.079	3.09	0.318	94.76	4.82	-0.235	22.38
Moving average models	990	90.7	66.16	1.068	2.97	0.318	96.15	4.65	-0.232	23.15
Momentum models	102	9.3	69.91	1.180	4.24	0.322	81.30	6.51	-0.269	14.87
Models with lag = 0	546	50.0	67.26	1.097	3.29	0.319	91.03	5.40	-0.245	20.80
Models with lag = 1	546	50.0	65.75	1.060	2.88	0.317	98.49	4.24	-0.225	23.96
					Corn futures contract					
t-statistic of the mean of the single returns										
< 1.0	991	90.8	14.53	0.453	3.38	0.191	88.43	6.70	-0.351	18.12
1.0 - <=2.0	101	9.2	35.19	1.138	3.32	0.160	104.96	3.08	-0.305	24.51
> 2.0	-	-	-	-	-	-	-	-	-	-
All models	1092	100.0	16.44	0.516	3.38	0.188	89.96	6.36	-0.347	18.71
Moving average models	990	90.7	16.36	0.511	3.17	0.187	92.03	6.05	-3.410	19.17
Momentum models	102	9.3	17.25	0.569	5.41	0.020	69.79	9.39	-0.400	14.25
Models with lag = 0	546	50.0	15.26	0.483	3.50	0.190	88.14	7.36	-0.367	16.87
Models with lag = 1	546	50.0	17.62	0.550	3.25	0.186	91.77	5.36	-0.326	20.56
					Wheat futures contract					
t-statistic of the mean of the single returns										
< 1.0	677	62.0	20.28	0.634	3.19	0.189	88.02	4.68	-0.279	26.87
1.0 - <=2.0	415	38.0	40.16	1.198	3.74	0.245	76.41	5.60	-0.239	21.49
> 2.0	-	-	-	-	-	-	-	-	-	-
All models	1092	100.0	27.84	0.848	3.40	0.210	83.61	5.03	-0.264	24.82
Moving average models	990	90.7	28.51	0.866	3.20	0.209	86.20	4.65	-0.251	25.92
Momentum models	102	9.3	21.26	0.674	5.29	0.221	58.45	8.75	-0.391	14.23
Models with lag = 0	546	50.0	28.42	0.862	3.61	0.215	81.29	5.74	-0.280	23.11
Models with lag = 1	546	50.0	27.25	0.835	3.19	0.206	85.93	4.32	-0.249	26.54
					Rice futures contract					
t-statistic of the mean of the single returns										
< 1.0	1068	97.8	16.43	0.513	2.65	0.171	95.40	5.69	-0.158	28.11
1.0 - <=2.0	24	2.2	27.94	1.242	6.24	0.205	47.21	10.65	-0.215	12.50
> 2.0	-	-	-	-	-	-	-	-	-	-
All models	1092	100.0	16.68	0.529	2.72	0.172	94.34	5.80	-0.159	27.77
Moving average models	990	90.7	17.25	0.529	2.51	0.172	98.07	5.41	-0.154	29.00
Momentum models	102	9.3	11.18	0.530	4.80	0.166	58.19	9.60	-2.110	15.80
Models with lag = 0	546	50.0	17.43	0.586	2.94	0.174	90.79	6.33	-0.164	26.21
Models with lag = 1	546	50.0	15.94	0.490	2.51	0.169	97.89	5.26	-0.154	29.33

The picture is similar as regards the performance trend-following technical models in the three other commodity futures markets (see tables 7b to 7d in the annex). In most cases the models are profitable on average; however, there is a tendency of declining profitability over time. This tendency could indicate that markets become more efficient or that technical trading is increasingly based on intraday data instead of daily data (for a discussion of this issue see *Schulmeister*, 2009B and 2009C).

The fact that persistent commodity price trends occur "abnormally" frequently (causing technical trading to be profitable ex post) does not ensure the profitability of technical trading ex ante. If, e. g., a trader selects a model that would have performed best over the most recent past for trading over a subsequent period, then he might become a victim of his own "model mining" for the following reason.

The ex-post profitability of the best models consists of two components. The first stems from the "normal" non-randomness of asset prices, namely, the occurrence of persistent price trends. The second component stems from the selection or over-fitting bias since a part of the ex-post profits of the best models would have been produced only by chance (*Sullivan-Timmerman-White*, 1999). Now, if the "optimal" profitability of a selected model is mainly the result of this "model mining" then this model will perform much worse over the subsequent period. However, if the in-sample profitability stems mainly from the exploitation of "usual" exchange rate trends then it might be reproduced out of sample.

In order to investigate this matter, the following exercise was carried out. In a first step the 25 best models are identified on the basis of their ex-post performance (measured by the net rate of return) over the most recent sub-period. Then the performance of the selected models is simulated over the subsequent sub-period.

Table 7a shows that the ex-ante-performance of the 25 best models in the oil futures market was significantly better in most sub-periods than on average of all models: If one had selected the 25 best performing models for trading in the subsequent period one would have made significant profits with the exception of the period between 2001 and 2004 (over the entire period between 1993 and June 2011, the ex-ante return of the 25 best models amounts to 9.62% per year whereas the average return over all models is only 6.07% - table 8a).

In the case of trading corn, wheat and rice futures, the ex-ante-performance of the 25 models which performed best over the preceding period is similar to the average ex-post-performance of all models (see tables 7b to 7d as well as 8b to 8d in the annex).

Tables 8a to 8d summarize the means over the gross rates of returns and over the three ratios of the profitability components of all models as well as of the 25 best models ex post and ex ante. The t--statistics test for the significance of the difference between the means of the best models and the means of all models.

Table 7a: Performance of technical trading systems by sub-periods

Ex post and ex ante

WTI crude oil futures contract, daily data, 1989 to 2011 (June)

		All models	25 best models Ex post	25 best models Ex ante
1989-1992	Gross rate of return	30.97	50.99	
	t-statistic	1.459	2.220	
	DPP	89.39	88.33	
	Share of profitable models	99.7	100.0	
1993-1996	Gross rate of return	9.68	25.61	12.94
	t-statistic	0.661	1.510	0.872
	DPP	79.36	74.76	75.95
	Share of profitable models	93.8	100.0	100.0
1997-2000	Gross rate of return	12.39	35.77	26.63
	t-statistic	0.679	1.536	1.191
	DPP	86.24	68.80	68.28
	Share of profitable models	96.8	100.0	100.0
2001-2004	Gross rate of return	3.54	17.95	-3.95
	t-statistic	0.245	1.191	-0.289
	DPP	81.76	70.55	61.33
	Share of profitable models	74.2	100.0	40.0
2005-2008*)	Gross rate of return	5.79	18.17	6.47
	t-statistic	0.332	0.992	0.385
	DPP	73.90	62.42	66.03
	Share of profitable models	84.4	100.0	84.0
2008-2011**)	Gross rate of return	-1.06	23.87	6.02
	t-statistic	-0.030	0.598	0.156
	DPP	80.08	56.37	62.67
	Share of profitable models	46.9	100.0	72.0

*) January 2005 - June 2008. - **) July 2008 - June 2011.

In the oil futures markets the mean annual rate of return of the (ex-post) best models (24.3%) is four times higher than the mean over all models (6.07%). This high profitability is due to the means of all three ratios of the profit components being significantly higher in the case of the 25 best models in sample than in the case of all models. Similar results are obtained in the case of trading corn, wheat and rice futures except for one result: The ratio between the duration of profitable positions and unprofitable positions is lower than on average over all models (tables 8b to 8d in the annex).

This profitability pattern of the ex-post best models cannot be reproduced ex ante. In the oil futures market, the mean ratio between the daily return during profitable positions and during unprofitable positions is significantly lower in the case of the best models out of sample as compared to the average ratios over all models. This observation holds true also for trading wheat futures (table 8c). Whereas the ratio between the duration of profitable positions and unprofitable positions is significantly higher in the case of oil futures trading, it is significantly lower in the case of wheat and rice futures trading (tables 8). Hence, the ex-ante-profitability of technical commodity futures trading is due to the optimization of the ratio between the number of profitable and unprofitable positions. This ratio is significantly higher in the case of the 25 ex-ante best models as compared to the average over all models in three out of four markets, e. g., oil, corn and wheat futures markets (tables 8a and 8b to 8c in the annex).

Table 8a: Distribution of trading systems by the gross rate of return and by the ratio of profit components over sub periods

WTI crude oil futures contract, 1993 to 2011 (June)

Variable	Mean	S.D.	t-statistic
		All models	
		N=5460	
Gross rate of return	6.07	9.03	
NPP/NPL	0.544	0.200	
DRP/DRL	0.705	0.229	
DPP/DPL	3.783	1.399	
		The 25 most profitable models: Ex post	
		N=125	
Gross rate of return	24.27	7.12	28.068
NPP/NPL	0.713	0.226	8.300
DRP/DRL	0.781	0.237	3.558
DPP/DPL	4.466	1.920	3.953
		The 25 most profitable models: Ex ante	
Gross rate of return	9.62	13.66	2.894
NPP/NPL	0.614	0.241	3.225
DRP/DRL	0.641	0.229	-3.075
DPP/DPL	4.071	1.654	1.929

NPP (NPL). . .Number of profitable (unprofitable) positions per year.
DRP (DRL). . .Return per day during profitable (unprofitable) positions.
DPP (DPL). . .Average duration of profitable (unprofitable) positions.
The t-statistic tests for the significance of the difference between the mean of the four variables over the 100 cases of the best models (in and Ex ante) and the respective mean over the 4368 cases of all models.

11. Price effects of the use of technical trading systems in commodity futures markets

In a first step an index of the aggregate transactions and positions of the 1092 technical models is calculated. Based on these indices, the concentration of transactions in terms of buys and sells and of position holding in terms of long and short is documented. Finally, the relationship between the level and the change of the net position index and the subsequent commodity price movements is analyzed.

11.1 The aggregation of trading signals

The open positions of the 1092 models are aggregated as follows. For every trading day the number +1 (-1) is assigned to any long (short) position of each single model. The net position index (PI) is then calculated as the sum of these numbers over all models divided by the number of models (1092). Hence, an index value of +100 (-100) means that 100% of the models hold a long (short) position. A value of 90 (-90) indicates that 95% of the models are long (short) and 5% short (long).[17])

The net transaction index (TI) is the first difference of the net position index. Its theoretical maximum (minimum) value is twice as high (in absolute terms) as in the case of the net position index since the number of transactions is always twice the number of (changed) open positions. The extreme value of +200 (-200) would be realized if all 1092 models change the open position from short to long (from long to short) between two consecutive trading days (implying 2048 transactions in either case).

In order to investigate the extent to which the signals from technical models balance each other, the components of the net transaction index are also documented, i.e., the number of buys and sells on each trading day (divided by the number of all models).

11.2 Similarities in position taking of technical models

Figure 29 shows the gradual adjustment of the 1092 technical models to oil futures price movements between January 2007 and June 2011 (figures 30 to 32 display the same relationship for corn, wheat and rice futures). On February 7, 2008, e. g., all models hold a short position due to a proceeding decline in oil futures prices. The subsequent price rise causes the models to gradually switch their position from short to long, the "fast" models at first, the "slow" models at last. On February 21, all models hold a long position. During this transition period from short to long, technical models exert an excess demand on oil futures since any switch implies two buy transactions, one to close the (former) short position, and one to open the (new) long position.

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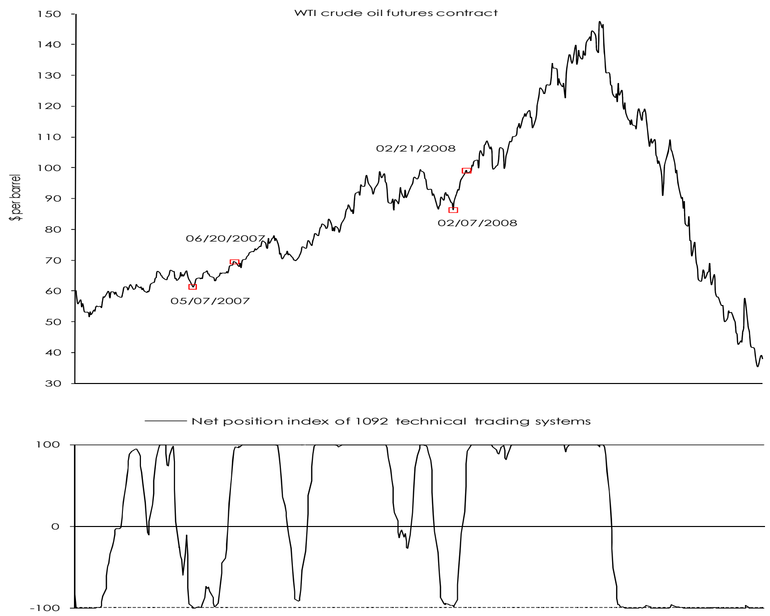
[17]) The percentage share of models holding a long position can generally be derived from the value of the net position index (PI) as [PI+100]/2. So, if PI equals 0, then half the models signal a long position and half signal a short position.

Figure 29: Aggregate trading signals of 1092 technical models and the dynamics of oil futures prices

2007 to 2008



2009-2011(June)

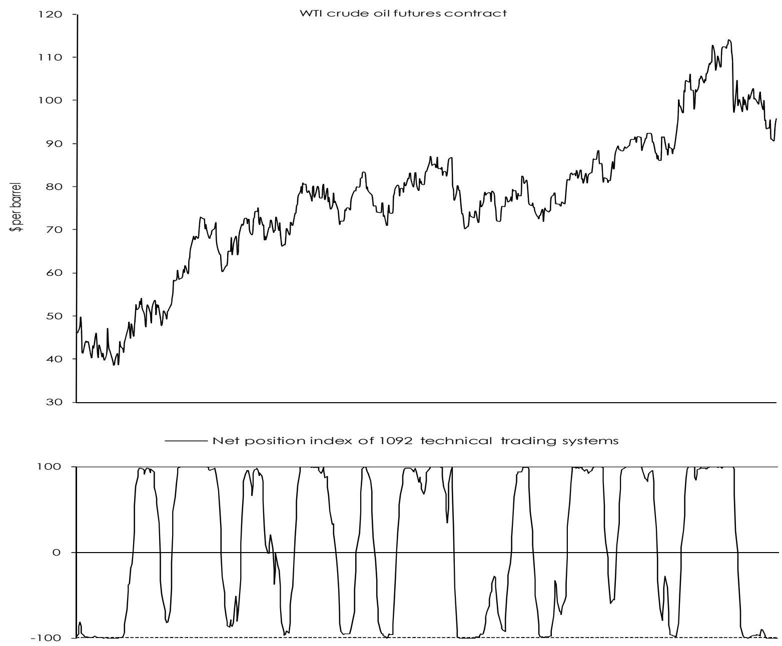
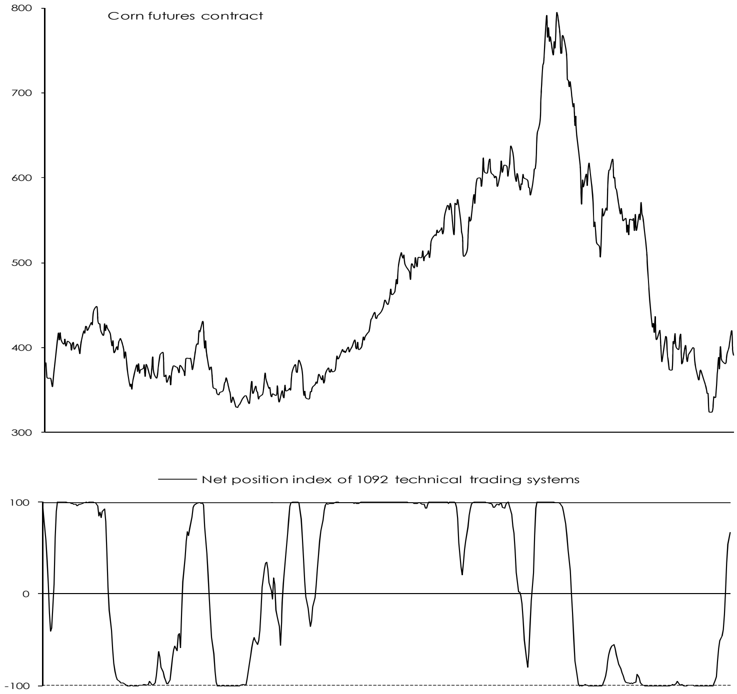


Figure 30: Aggregate trading signals of 1092 technical models and the dynamics of corn futures prices

2007 to 2008



2009-2011 (June)

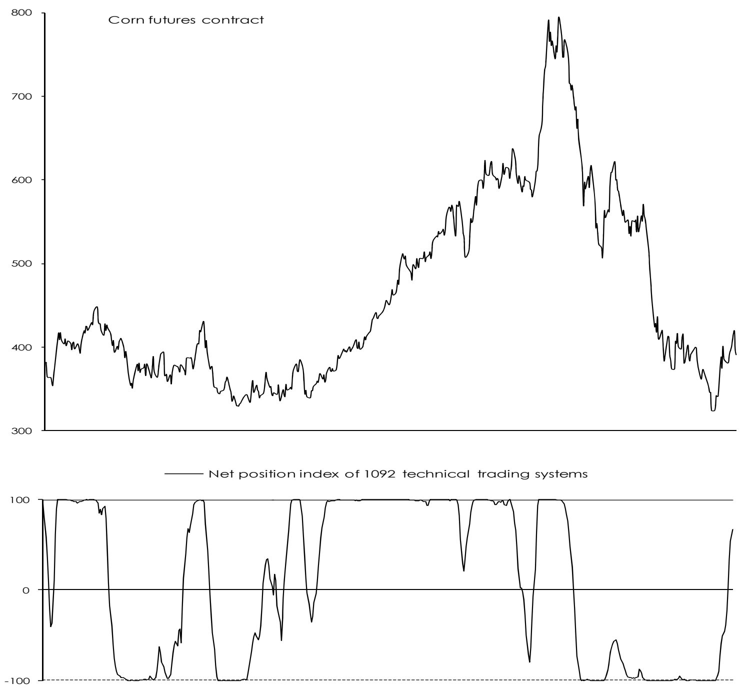
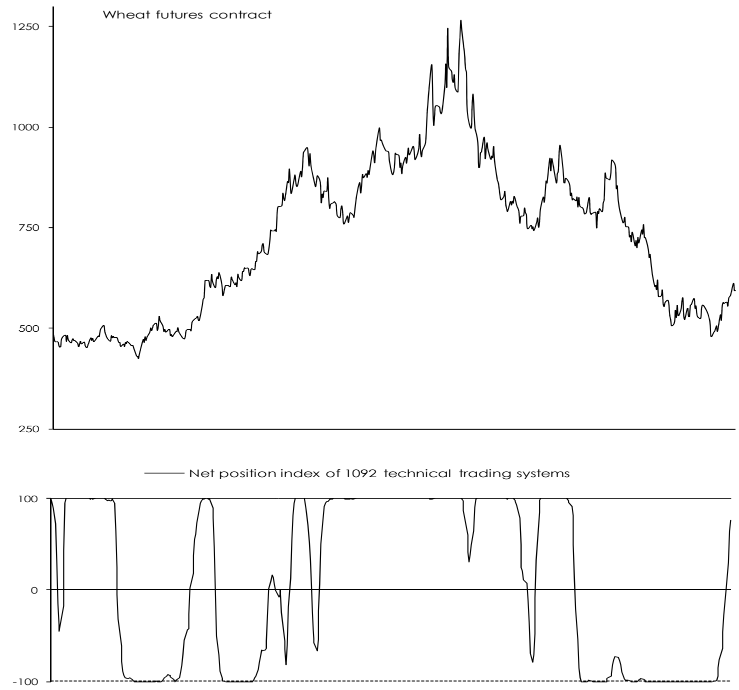


Figure 31: Aggregate trading signals of 1092 technical models and the dynamics of wheat futures prices

2007 to 2008



2009 to 2011 (June)

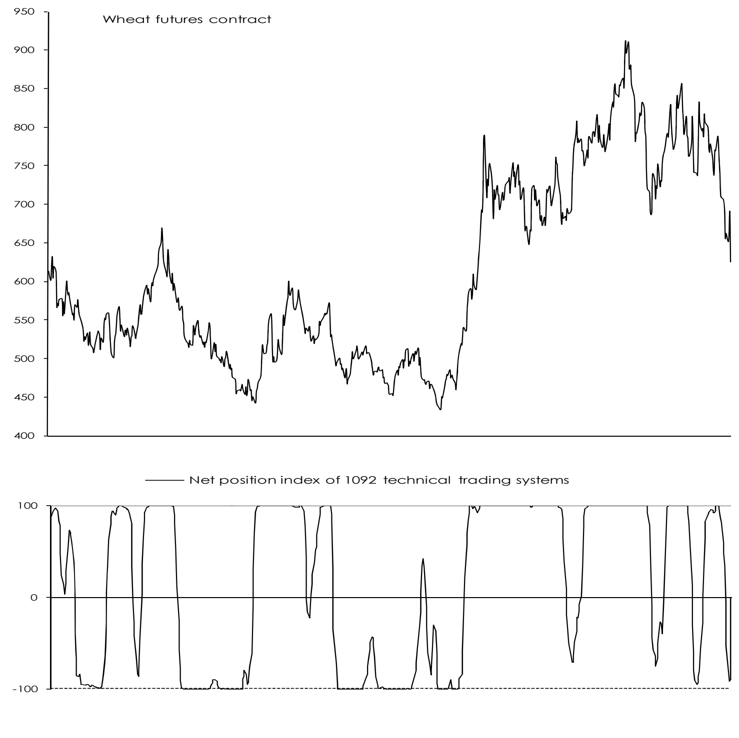
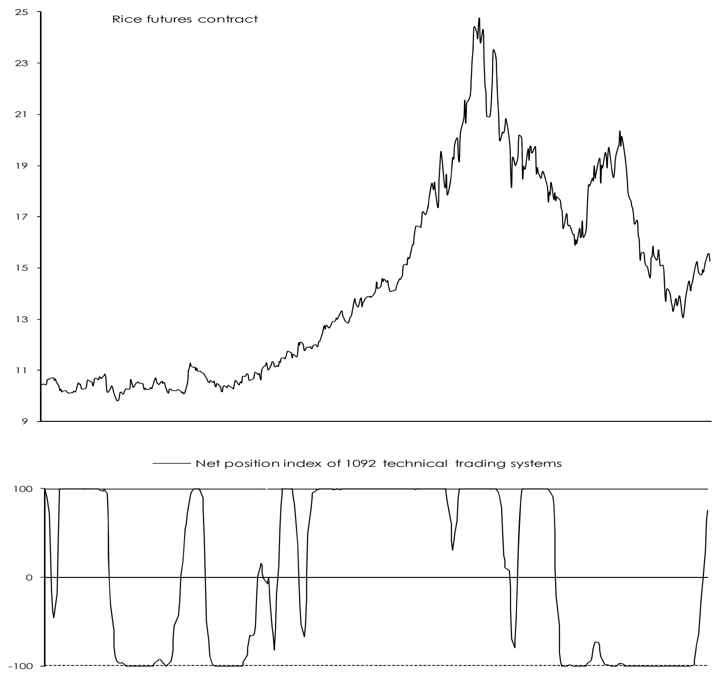
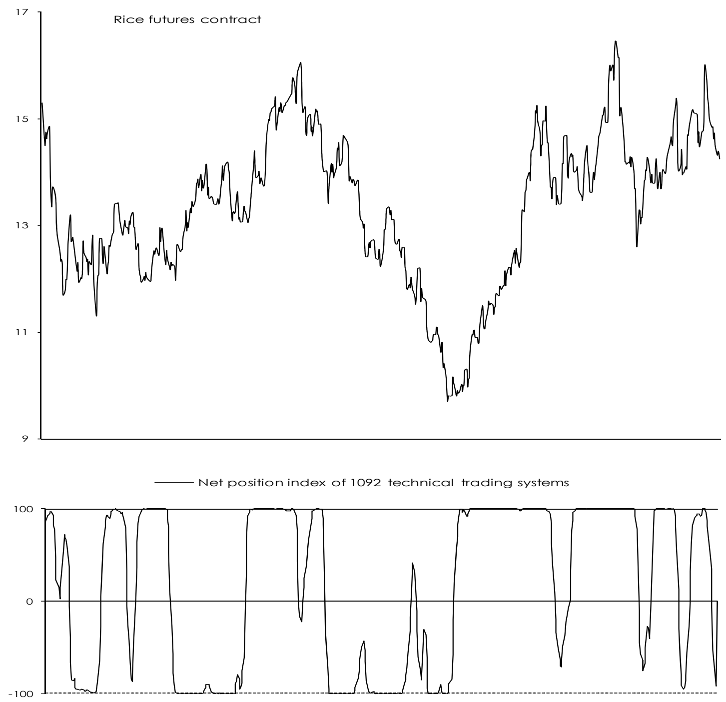


Figure 32: Aggregate trading signals of 1092 technical models and the dynamics of rice futures prices

2007 to 2008



2009 to 2011 (June)



An investigation into the trading behaviour of the 1092 technical models over the entire sample reveals the following. First, most of the time the great majority of the models are on the same side of the market. Second, the process of changing open positions usually takes off 1 to 3 days after the local futures price minimum (maximum) has been reached. Third, it takes between 10 and 20 trading days to gradually reverse the positions of (almost) all models if a persistent futures price trend develops. Fourth, after all technical models have adjusted their open positions to the current trend, the trend often continues for some time. Figures 29 to 32 clearly demonstrate the gradual switching of technical models between long and short positions and the related price movements.

Table 9a: Distribution of time by positions and transactions of technical trading systems

Moving average and momentum models

WTI crude oil futures contract, 1989 to 2011 (June)

	Aggregate positions			
Net position index	Share in total sample period in %	Mean of the net position index	Mean of the gross position index	
			Long	Short
> 90	38.15	98.77	99.39	-0.61
70 - 90	6.47	81.18	90.59	-9.41
50 - 70	3.94	60.75	80.38	-19.62
30 - 50	3.46	39.69	69.85	-30.15
30 - 10	3.21	20.04	60.02	-39.98
-10 - 10	2.98	-0.69	49.66	-50.34
-30 - -10	3.03	-19.58	40.21	-59.79
-50 - -30	3.14	-39.80	30.10	-69.90
-70 - -50	3.69	-61.01	19.50	-80.50
-90 - -70	5.59	-81.39	9.30	-90.70
< -90	26.34	-98.47	0.76	-99.24
Total	100.00	12.75	56.37	-43.63

	Aggregate Transactions			
Net transaction index	Share in total sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
			Long	Short
> 70	0.00	0.00	0.00	0.00
50 - 70	0.04	53.21	53.39	-0.18
30 - 50	0.94	35.16	35.68	-0.52
30 - 10	10.48	18.00	19.09	-1.10
-10 - 10	76.75	0.02	1.50	-1.48
-30 - -10	10.82	-17.69	0.99	-18.67
-50 - -30	0.89	-36.32	0.38	-36.70
-70 - -50	0.09	-57.33	0.07	-57.40
< -70	0.00	0.00	0.00	0.00
Total	100.00	-0.04	3.62	-3.65

Table 9a quantifies some of these observations for the case of oil futures trading (see also the analogous tables for corn, wheat and rice futures trading in the annex). On 38.2% (26.3%) of all days more than 95% of the models hold a long (short) position. Hence, on 64.5% of all days more than 95% of the models hold the same – long or short – position. By contrast, periods during which short positions and long positions are roughly in balance seldom occur (the position index lies between 10 and –10 on only 3.0% of all days).

On 76.8% of all days less than 5% of the models execute buy or sell signals (TI lies between 10 and –10). There are two reasons for that. First, the majority of the models hold the same position for most of the time. Second, the process of changing open positions evolves only gradually.

Table 10a: Similarity of different types of 1092 technical trading systems in holding open positions

WTI crude oil futures contract, 1989 to - 2011 (June

	Relative share of models holding the same - long or short - position		
	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	61.12	72.24	80.42
1.0 - <=2.0	59.65	65.47	71.92
> 2.0	49.96	57.22	61.88
By stability			
Stable models	58.74	67.08	75.52
Unstable models	57.93	64.01	71.02
By duration of profitable positions			
Short-term	50.00	58.35	69.01
Medium-term	67.63	71.98	77.37
Long-term	76.13	81.82	86.22
All models	58.81	64.49	71.67

Table 9a also shows that the signals produced by technical models would cause their users to trade very little with each other. If the models move relatively fast from short to long positions (10<TI<30) or vice versa (-10>TI>-30) then almost 20 times more buy (sell) signals are produced than sell (buy) signals. On days when less than 5% of the models trade (10>TI>-10) roughly the same number of buys and sells are executed, however, their size is very small.

Table 10a shows the great similarity in the trading behaviour of technical models (see also the analogous tables 10b to 10d for corn, wheat and rice futures trading in the annex). E. g., more than 90% of all models hold the same open position on 71.7% of all days. The trading behaviour of long-term models is significantly more similar than that of short-term models. This is also true – though to a lesser extent – for stable models relative to unstable models (the former are those which are profitable over each of the 6 sub-periods).

The empirical evidence presented in figures 29 to 32, in tables 9a to 9d and in tables 10a to 10d suggests the following: The aggregate trading behaviour of technical trading systems strengthen and lengthen commodity price trends. At the same time, technical models aim at exploiting price trends in commodity markets (as in any asset market), and they are often very successful in "riding" commodity price trends. This hypothesis shall be explored more in detail in the following chapter.

11.3 The interaction between technical trading and commodity price movements

At first, the possible interactions between the aggregate trading behaviour of technical models and the development of a commodity price trend shall be discussed in a stylized manner taking an upward trend as example.

The first phase of a trend (marked by A and B in figure 33) is brought about by the excess demand of non-technical traders, usually triggered off by some news (causing news-based traders to expect a dollar appreciation and, hence, to open long dollar positions).

During the second phase of an upward trend (between B and C in figure 33) technical models produce a sequence of buy signals, the fastest models at first, the slowest models al last. The execution of the respective order flows then contributes to the prolongation of the trend.

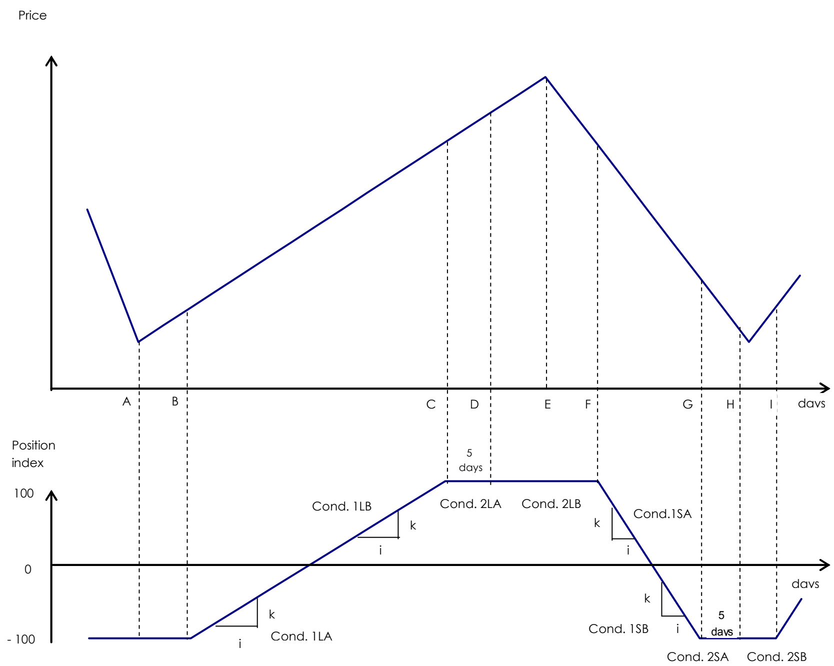
Over the third phase of the trend all technical models hold long positions while the trend continues for some time (marked by C and E in figure 33). Since technical models already hold a long position the prolongation of the trend is caused by an additional demand of non-technical traders, possibly amateur "bandwagonists" who jump later on trends than professional traders (in the case of foreign exchange trading, professionals consider bandwagon effects as one of the four most important factors driving exchange rates – see *Cheung-Chinn-Marsh*, 2004; *Cheung-Wong*, 2000; *Cheung-Chinn*, 2001).

As the price trend continues, the probability that it ends becomes progressively greater. This is so for at least three reasons. First, the number of traders who get on the bandwagon declines. Second, the incentive to cash in profits rises. Third, more and more contrarian traders consider the commodity overbought (oversold) and, hence, open a short (long) position in order to profit from the expected reversal of the trend.[18])

[18]) Note, that there are not only those contrarians who base their trading on qualifying assets as "overbought" or "oversold" but also technical traders who use "contrarian models" as described by *Kaufman*, 1987. An analysis of the performance of these models in the stock market is provided by *Schulmeister*, 2009C.

When the upward trend finally comes to an end, mostly triggered by some news, a countermovement usually takes off. With some lag technical models start to close the former positions and open new counter-positions (on day F in figure 22).

Figure 33: Asset price trends and aggregate positions of technical models



For technical trading to be overall profitable it is necessary that upward (downward) trends continue for some time after the models have taken long (short) positions. This is so for three reasons. First, all models have to be compensated for the losses they incur during "whipsaws". Second, fast models often make losses during an "underlying" asset price trend as they react to short-lasting counter-movements. Third, slow models open a long (short) position only at a comparatively late stage of an upward (downward) trend so that they can exploit the trend successfully only if it continues for some time.

In order to explore the interaction between commodity price movements and the trading behaviour of technical models the following exercise is carried out. At first, some conditions concerning the change and the level of the net position index are specified. These conditions grasp typical configurations in the aggregate trading behaviour of technical models. Then the difference between the means of the commodity price changes observed under these conditions from their unconditional means is evaluated.

The first type of conditions concerns the speed at which technical models switch their open positions from short to long (condition 1L) or from long to short (condition 1S). Condition 1L comprises all cases where 12.5% (25%, 50%) of all models have been moving continuously from short to long positions over the past 3 (5, 10) business days (PI increases monotonically).

In addition, the condition 1L excludes all cases where more than 97.5% of the models hold long positions (these cases are comprised by condition 2L). Hence, condition 1L is defined as follows.

Condition 1L: $[PI_t\text{-}PI_{t\text{-}i}]>k \cap [PI_{t\text{-}n}\text{-}PI_{t\text{-}n\text{-}1}]\geq 0 \cap [PI_t\leq 95]$
k....25, 50, 100
i.......3, 5, 10
n......0, 1, ... (i-1)

Condition 1S comprises the analogous cases of changes positions from long to short.

Condition 1S: $[PI_t\text{-}PI_{t\text{-}i}]<\text{-}k \cap [PI_{t\text{-}n}\text{-}PI_{t\text{-}n\text{-}1}] \leq 0 \cap [PI_t \geq \text{-}95]$
k....25, 50, 100
i.......3, 5, 10
n......0, 1, ... (i-1)

Condition 2L(S) comprises all cases where more than 97.5% of all models hold long (short) positions:

Condition 2L(S): PI > 95 (PI < 95)

Figure 22 gives a graphical representation of the meaning of these four conditions (the subdivision of the conditions 1 and 2, marked by "A" and "B", will be discussed later).

For each day t on which these conditions are fulfilled the rate of change (CCP_t) between the current commodity price (CP_t) and the respective price j days ahead (CP_{t+j}) is calculated (j...5, 10, 20, 40). Then the means over the conditional commodity price changes are compared to the unconditional means over the entire sample and the significance of the differences is estimated using the t-statistic. This comparison shall examine if and to what extent the price continues to rise (fall) after 12.5% (25%, 50%) of technical models have changed their position from short (long) to long (short), and if and to what extent this is the case when 97.5% of all models hold long (short) positions.

For each day on which condition 1 is fulfilled also the price changes over the past 3 (5, 10) days are calculated and compared to the unconditional price changes. The purpose of this exercise is to estimate the strength of the interaction between commodity price movements and the simultaneous execution of technical trading signals induced by these movements.

Table 11a shows that the conditions 1 are rather frequently fulfilled. E. g., in 630 (667) cases more than 12.5% of all models change their open positions from short to long (from long to short) within 3 business days (conditions 1L(S) with k=25 and i=3, abbreviated as condition 1L(S)[25/3)]). In 485 (500) cases more than 25% of the models change their open position in the same direction within 10 business days. Conditions 1L(S)[100/10] are realized in only 293 (333) cases. The number of cases fulfilling conditions 1 are the smaller the larger is the parameter k. E. g., if k=100 then the possible realizations of condition 1L are restricted to a range of the position index between 5 and 95, however, if k=25 then condition 1L could be fulfilled within a range of the position index between -70 and 95.

Conditions 2 occur much more frequently than conditions 1. In 1963 cases more than 97.5% of all models hold a long position (condition 2L). Since the crude oil price was rising over the entire sample period, condition 2S was less frequently realized (1420 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 4598 days out of the entire sample of 5640 days.[19]) These conditions are realized similarly often when simulating technical trading of corn, wheat and rice futures (tables 11b to 11d). This behaviour of 1092 technical models can hardly be reconciled with the hypothesis that daily commodities prices follow a (near) random walk.

The means of commodity price changes (CCP_t) on all days satisfying condition 1 over the past 3 (5,10) days are very much higher than the unconditional means over the entire sample period. E. g., the average (relative) crude oil price change over 5 consecutive days amounts to 0.26% between 1989 and June 2011, however, when 25% of the technical models turn their open position from short to long within 5 days the oil futures price rate increases on average by 3.76%. This highly significant difference (t-statistic: 19.9) can be explained as the result of the simultaneous interaction between oil futures price movements and the changes of open positions by technical models (table 11a).

The means of the conditional oil futures price changes over the 5 (10, 20, 40) days following the realization of condition 1L have the same (positive) sign as the preceding change in the position index and are significantly different from the unconditional means (table 11a). However, after the conditions 1S are realized (i.e., when technical models switch their position from long to short), the conditional price changes have in all 12 cases the wrong sign, in 6 cases the t-statistic is even highly significant.

Over the first 5 to 40 days subsequent to the realizations of condition 2L, i.e., when 97.5% of all models hold a long position, oil futures prices tend to continue to rise (with the exception of the time span of 20 days), however, this tendency is statistically insignificant. Downward trends last longer on average than upward trends (figure 29). As a consequence, after 97.5% of all models have taken short positions (condition 2S) oil futures prices decline stronger than on average; this difference is statistically significant over all time spans from 5 to 40 days.

[19]) In order to avoid double-counting only the cases of conditions 1L(S)[25/3] are considered as regards condition 1 – most cases satisfying condition 1 with k=50 or k=100 are a subset of the cases satisfying condition 1 with k=25

Table 11a: Aggregate trading signals and subsequent oil futures price movements

Corn futures contract, 1993 to 2012 (June)	Time span j of CCP	More than 12.5% (25%, 50%) of all models change open positions in the same direction within 3 (5,. 10) business days					
k	j	From short to long positions (condition 1L)			From long to short position (condition 1S)		
		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
25	-3	630	2.4042	17.0542	667	-2.2794	-16.2946
	5	630	0.6563	2.0024	667	0.7121	2.5511
	10	630	1.4554	3.4319	667	0.8866	1.5927
	20	630	3.0915	5.2639	667	2.1581	3.0662
	40	630	4.4966	4.0857	667	4.7052	4.4455
50	-5	485	3.7646	19.8889	500	-3.4651	-19.4271
	5	485	0.7893	2.4003	500	0.9261	3.3712
	10	485	1.8570	4.2387	500	0.7787	1.0255
	20	485	3.2469	4.7667	500	2.3420	3.1500
	40	485	5.2711	4.5317	500	4.8340	4.0564
100	-10	293	6.8166	24.0140	333	-6.0908	-25.5634
	5	293	0.8749	2.3182	333	0.8167	2.3823
	10	293	1.9585	3.5388	333	0.6907	0.5837
	20	293	2.6987	2.7186	333	2.3980	2.6843
	40	293	4.9754	3.0787	333	5.6796	4.4269
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1963	0.4174	1.2849	1338	-0.3034	-3.4083
	10	1963	0.7044	1.2302	1338	-0.5800	-4.9492
	20	1963	1.0176	-0.0004	1338	-0.9246	-5.9434
	40	1963	2.1849	0.2817	1338	-1.2485	-6.7549

The table presents the means of commodity price changes over i business days (CCP_{t+j}) under four different conditions.
Condition 1L (S) comprises all situations where more than 12.5% (25%, 50%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) business days. The moves are restricted to a range of the position index PI_t between 95 and –95.
Condition 2L (S) comprises all situations beyond this range. i.e., where more than 97.5% of all trading systems hold long (short) positions.
More formally these conditions are defined as follows:

Condition 1L (S):
$[PI_t - PI_{t-i}] > k\ (<- k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0\ (\leq = 0) \cap [-95 \leq PI_t \leq 95]$
k......25, 50, 100
i........3, 5, 10
n.......0, 1, ... t_{i-1}

Condition 2L (S):
PI > 95 (< -95)

$CCP_{t+j} = 100 * [CP_{t+j} - CP_t] / CP_t$ for j........5, 10, 20, 40
$CCP_{t+j} = 100 * [CP_t - CP_{t+j}] / CP_t$ for j.......-3, -5, -10

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

These results imply the following "stylized facts" about the interaction between oil futures price movements and the aggregate trading behaviour of (trend-following) technical models:

- When the models are switching positions from short to long, prices continue to move in the direction congruent with the switch for a comparably short period. When finally (almost) all models have taken a long position, prices continue to rise but at a slower speed.
- When the models are switching positions from short to long there often occur short-term trend reversals. Only when (almost) all models are holding short positions do downward trends continue for some time at a significantly higher speed than on average over the whole period.

The figure 29 visualizes this pattern. During bear markets, the single downward trends are particularly persistent, whereas during bull markets upward trends last comparatively shorter but occur more often. These observations suggest that short-term models would perform comparatively better during bull markets and long-term models would perform better during bear markets. However, it is hard to know in advance if a bull market or a bear market will develop.

In the case of rice futures trading, the interaction between the aggregate trading behaviour of technical models and subsequent price movements is more pronounced than in the case of oil futures trading (compare table 11d in the annex to table 11a). When the models change their open positions at a certain speed then the rice futures price changes much stronger than on average in the direction congruent with the models' transactions. When almost all models are holding long (short) positions, rice futures prices continue to rise (fall) for an extended period of time stronger than on (the unconditional) average.

This pattern is much less pronounced in the case of corn futures trading, and it is practically non-existing in the case of wheat futures trading (see tables 11b and 11c in the annex). At the same time, the profitability of the technical models investigated is by far greater in the oil and rice futures market as compared to the corn and wheat futures markets. If one assumes that the better performing models will be more often used in practice than the poorly performing models then one should expect a stronger interaction between aggregate trading signals and subsequent price movements in the case of (highly) profitable models as compared to poorly performing models.

Finally, the following exercise is carried out. Each of the four phases of technical trading as defined by the conditions 1L(S) and 2L(S) is divided into two sub-phases by the (additional) conditions A and B (the parameters of condition 1 are set at k=50 and i=5). The meaning of the (sub)conditions A and B is explained as follows, taking an upward price trend as example.

Condition 1LA comprises all cases where 25% of all models have changed their positions from long to short within 5 days and where at the same time still less than 50% of the models hold long positions. Hence, condition 1LA covers the first phase of reversing technical positions after the commodity price has started to rise (see figure 33).

Condition 1LB comprises the second phase of position changes, i.e., when the price trend has gained momentum so that already more that 50% of the models are holding long positions.

Condition 2LA covers the third phase in the trading behaviour of technical models during an upward trend, namely, the first 5 business days after more than 97.5% of all models have opened long positions.

Condition 2LB comprises the other days over which 97.5% of all models keep holding long positions, i.e., the fourth and last phase of a trend (towards its end, trend-following models still hold long positions while the commodity price has already begun to decline as between E and F in figure 33).

The size of the conditional ex-ante oil futures price changes differs strongly across the four phases of an upward trend (table 12a). When 25% of the models have switched from short to long positions and more than 50% of the models are still short (condition 1LA) the price rise often persists. Hence, the means of the conditional price changes following the realization of conditions 1LA is significantly higher than the unconditional means over time spans from 5 to 40 days.

The oil futures prices continue to rise after the price trend has gained momentum (condition 1LB). After the first 5 days when 97.5% of all models have taken long positions (condition 2LA) When and remain so following the realizations of (which are restricted to the). Oil futures prices changes subsequent to the realizations of condition 2LB are in 3 out of 4 cases significantly negative. This result reflects the following fact: The longer a price trend lasts, the higher becomes the probability of a reversal.

First 5 business day when 97.5% of all models hold short positions. This result confirms the presumption derived from table 11a, namely, that the interaction between aggregate trading signals and oil price dynamics is stronger during upward price trends as compared to downward trends.

Tables 12b to 12d in the annex show that the relationship between switching or holding open positions and subsequent commodity price movements is closest in the case of rice futures. This relationship is much less pronounced in the case of corn futures and practically non-existing in the case of wheat futures. This result can - at least in part – be explained by the different profitability of the selected models in the four commodity futures markets (as already discussed in the context of tables 11a to 11d).

The results presented in this chapter let one conclude the following. There prevails a destabilizing interaction between the widespread use of technical trading systems in commodity futures markets and the overshooting dynamics of commodity prices. However, the strength of this interaction varies across markets. Based on the selected 1092 models, this interaction is strongest in the rice and oil futures markets, it is much weaker in the corn futures market, and it is practically non-existing in the wheat futures market.

Table 12a: Eight phases of technical trading and oil futures price movements

Conditions for CCPt + j	Time span j of CCPt + j	(Increasing) Long positions (Conditions .L.)			(Increasing) Short position (Conditions .S.)		
(= Phases of Technical trading)		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
1A	5	122	1.2228	1.9953	360	0.9927	3.2409
1B	5	363	0.8020	2.2705	140	0.6104	0.9376
2A	5	778	0.4867	1.3021	579	0.2590	-0.0016
2B	5	1185	0.3317	0.4811	759	-0.2409	-2.0713
1A	10	122	2.2498	2.7628	360	0.8926	1.2453
1B	10	363	1.9213	3.9552	140	0.5607	0.1268
2A	10	778	0.9311	1.8510	579	0.6575	0.5997
2B	10	1185	0.5221	0.1177	759	-0.4773	-3.2280
					0		
1A	20	122	3.7333	3.0434	360	3.0413	4.0864
1B	20	363	3.1917	4.2544	140	0.9978	-0.0284
2A	20	778	1.4680	1.4294	579	1.0756	0.1440
2B	20	1185	0.4770	-1.8413	759	-0.2606	-2.8243
1A	40	122	6.7640	3.5859	360	5.6612	4.6961
1B	40	363	4.8414	3.6785	140	3.0358	0.8494
2A	40	778	2.4467	0.7518	579	3.3579	2.2484
2B	40	1185	1.5296	-1.4049	759	-0.6087	-3.8542

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 50 and i = 5 (see Table 12a) is divided into two sub-phases by the conditions A and B:

Condition 1L (S): More than 25% of all trading systems have been moving from short to long (long to short) positions over the past five business days within the range $\{-95 \le PI_t \le 95\}$ and...

Condition 1L (S) A: Less than 50% of the models hold long (short) positions. i.e. $PI_t \le 0$ ($PI_t \ge 0$).

Condition 1L (S) B: More than 50% of the models hold long (short) positions. i.e. $PI_t \ge 0$ ($PI_t \le 0$).

Condition 2L (S): More than 97.5% of all trading systems hold long (short) positions. i.e. $PI_t > 95$ ($PI_t < 95$).

Condition 2L (S) A: Comprises the first five business days for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other days for which condition 2L (S) holds true.

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Oil futures price movements subsequent to the four conditions of technical trading during downward price trends differ from the respective movements during upward trends in particular in one respect (table 12a). The means of the conditional ex-ante price changes have the same (negative) sign as the preceding change in the position index and are significantly different from the unconditional means only under condition 2SA (i.e., during the

12. Hypothetical and actual position taking in US commodity futures markets

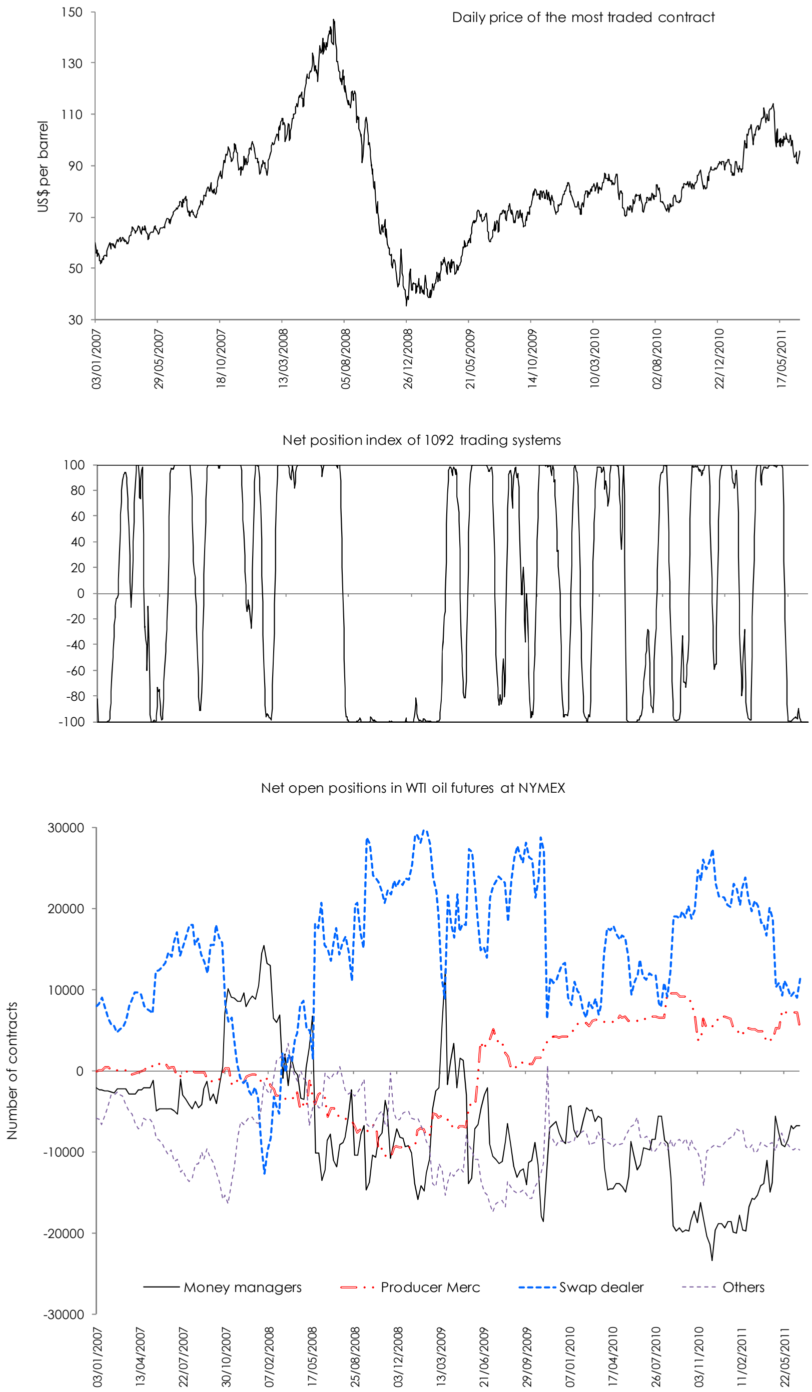
Figures 34 to 37 display daily futures prices of crude oil, corn, wheat and rough rice, the (hypothetical) daily net position index of the 1092 trading systems in the four futures markets and the actual (weekly) net open positions of 4 groups of participants in US derivatives exchanges (as documented by the US Commodity Futures Trading Commission in its "Disaggregated Commitment of Traders" report - DCOT). The charts cover the period 2007 to mid-2011, and, hence, the period of the widest fluctuations of the futures prices of oil, corn, wheat and rice (the CFTC has been publishing the DCOT data only since the second half of 2006).

There does not prevail a clear relationship between commodity price dynamics, the hypothetical position taking of 1092 trend-following trading systems and the actual open positions held by "Producers/merchant/processor/user" (those who deal with the physical commodity the real economy as producers or users – in the following called "producers/users"), "swap dealers" (holding long positions to hedge their short positions primarily vis-à-vis commodity index funds), "money managers" (primarily trading futures for speculative reasons) and the heterogeneous group of "other traders" (the net positions of all four groups add up to zero).

As argued in chapter 2, one cannot expect a clear relationship between the weekly net positions of certain groups of traders in US futures markets and the hypothetical positions held by 1092 trading systems based on daily data. The main reason for that consists of the fact that none of the four groups of market participants engage specifically or even exclusively with technical futures trading. However, the actual net positions (DCOT data) of that group of traders which concentrates the most on speculative activities, the money managers, is largely in line with the medium-term price trends and, hence, with the hypothetical positions of the 1092 technical trading systems as regards the three agricultural commodities.

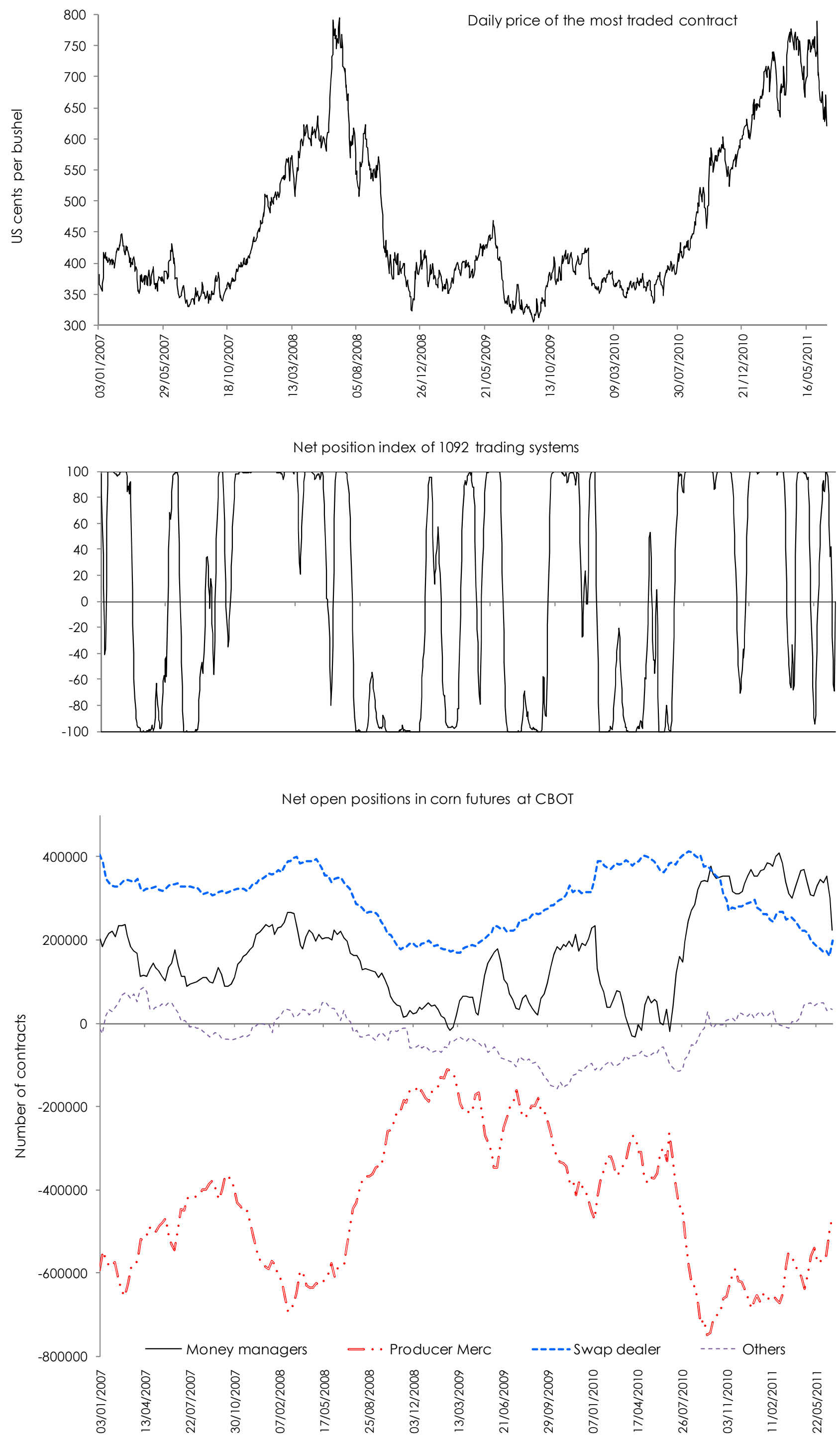
In the corn futures market, money managers increase their long positions strongly between October 2007 and March 2008, over the same period almost all technical models also hold long positions in reaction to the strong bull market (figure 35). The opposite development took place between May and November 2008 in line with the steep fall of corn futures prices. Figure 35 shows the coherence between upward price trends and the opening/holding of long positions by money managers for the periods between March and June 2009, September 2009 and June 2010, and between July and October 2010.

Figure 34: Price dynamics and net open positions in the oil futures market



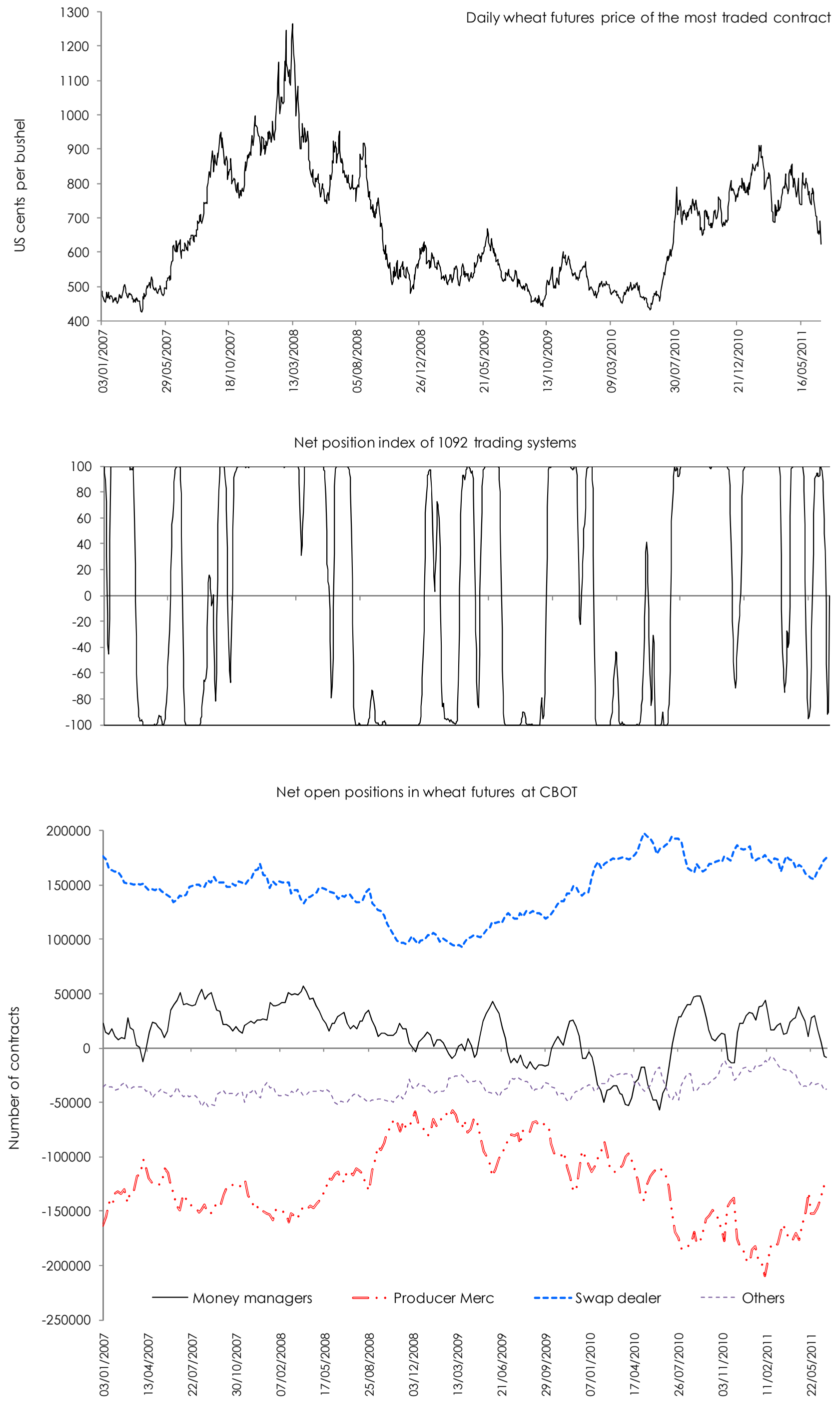
Source: NYMEX, CFTC.

Figure 35: Price dynamics and net open positions in the corn futures market



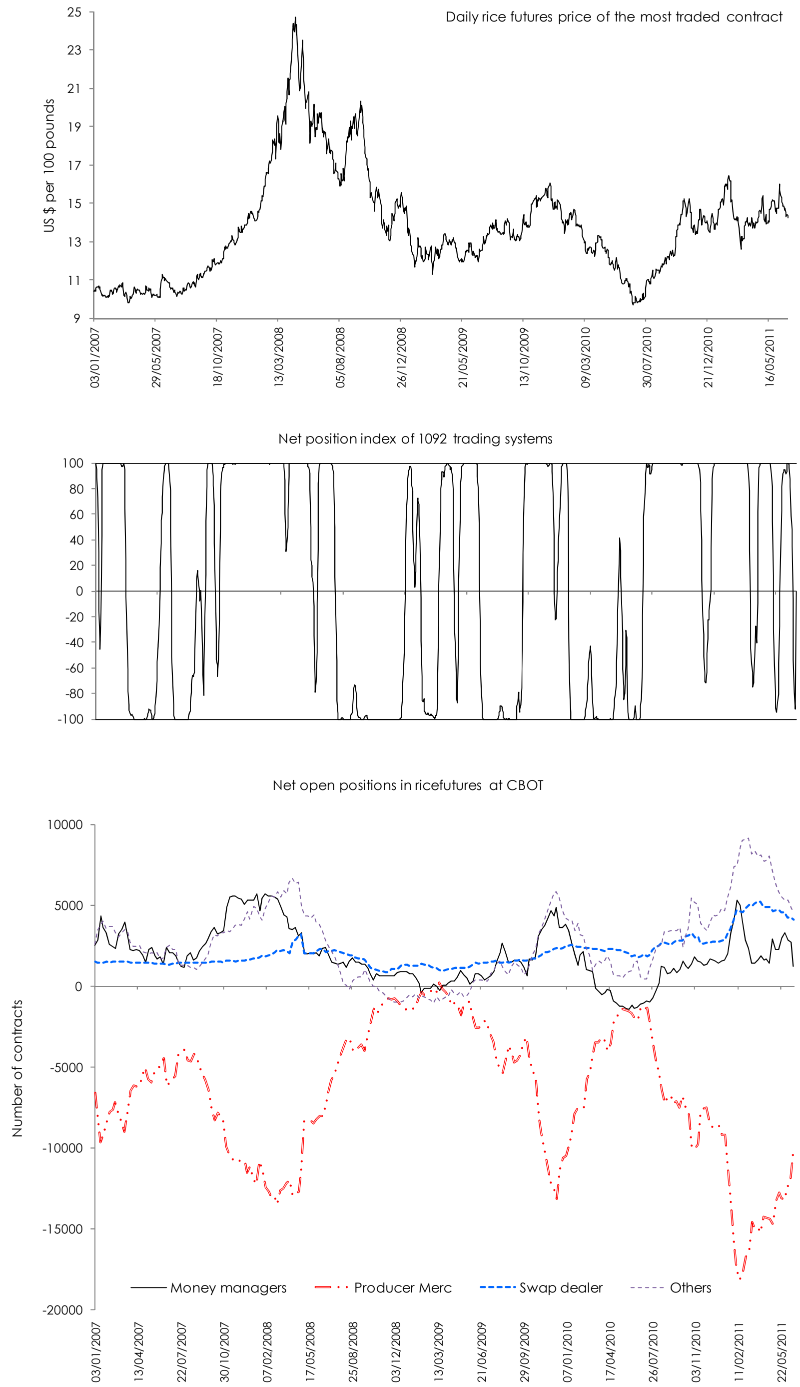
Source: NYMEX, CFTC.

Figure 36: Price dynamics and net open positions in the wheat futures market



Source: NYMEX, CFTC.

Figure 37: Price dynamics and net open positions in the rice futures market



Source: NYMEX, CFTC.

The position taking of swap dealers in the corn futures market also follows the long-term price trends (and most probably of agricultural commodities prices in general – see figures 36 and 37), but in a somewhat smoother fashion than the money managers (figure 35).

If one presumes that open positions of producers/users mainly reflect hedging activities then these activities are carried out in an asymmetric manner at a disadvantage of this group of agents (as turned out in hindsight). When corn prices started their bull market in October 2007 producers must have increased their short positions to a larger extent than users opened long positions so that the overall net (short) position of producers/users became bigger (in absolute terms - figure 35). A similar development took place between July and October 2010 when corn prices picked up again. By contrast, when corn prices started to fall steeply in April 2008, the net (short) position of producers/users declined significantly. The most reasonable explanation of this hedging behaviour might be that producers/users did not believe (ex ante) that bull and bear markets could develop which would be so persistent as turned later out to be the case since 2007.

Figures 36 and 37 show that the relationship between commodity price dynamics, the hypothetical position taking of 1092 trend-following trading systems and the actual open positions held by the four groups of agents in the wheat and rice futures markets is similar to that observed in figure 35 for corn futures.

This relationship is much different in the crude oil futures market, to a large extent because position taking has become dominated by swap dealers in this market (figure 34). At the same time it is difficult to find a rationale for the fact that this group of traders enlarged their net long positions over the second half of 2008 when oil prices were sliding persistently and stronger than ever before. This issue is not the only puzzle concerning oil futures position taking by groups of agents. Also the fact that the net positions of producers/users fluctuate little in the oil futures market and that money managers hold almost always a net short position needs further investigations.

References

Adaemmer, P., Bohly, M. D.,Stephan, P. M., Speculative Bubbles in Agricultural Prices, University of Muenster, Working Paper, January 2012

Bank for International Settlements, Triennial Central Bank Survey – Report on global foreign exchange market activities in 2010, Basel, December 2010.

Blancard , G. C., Coulibaly, D., Index Trading and Agricultural Commodity Prices: A Panel Granger Causality Analysis. Centre d'Etudes Prospectives et d'Info. Internationales (CEPII), CEPII Working Paper No. 2011–28, January 2012.

Brock, W., Lakonishok, J., LeBaron, B., "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns", The Journal of Finance, 1992, 47, 1731-1764.

Büyüksahin, B., Robe, M. A., Speculators, Commodities and Cross-Market Linkages, CFTC Working Paper, October 2010.

Chang, P. H. K., Osler, C. L., "Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecast", The Economic Journal, 109, October 1999, pp. 636-661.

Cheung, Y. W., Chinn, M. D., Marsh, I. W., "How do UK-Based Foreign Exchange Dealers Think Their Market Operates?", International Journal of Finance and Economics, 2004, 9 (4), 289-306.

Cheung, Y. W., Wong, C. Y. P, "A Survey of Market Practitioners' Views on Exchange Rate Dynamics", Journal of International Economics, 2000, 51, pp. 401-419.

Cheung, Y., Chinn, M. D., Currency Traders and Exchange Rate Dynamics: A Survey of the US Market", Journal of International Money and Finance", 2001, 20 (4), 439-471.

Commodity Futures Trading Commission (CFTC), Staff Report on Commodity Swap Dealers & Index Traders with Commission Recommendations, Washington, D. C., September 2008.

Davidson, P., Crude Oil Prices: "Market Fundamentals" or Speculation? "Crude Oil Prices: Challenge, 51(4), 2008.

De Grauwe, P., Grimaldi, M., The Exchange Rate in a Behavioural Finance Framework, Princeton University Press, Princeton, NJ, 2006.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J. (1990A), "Noise Trader Risk in Financial Markets", Journal of Political Economy, 1990, 98(4), pp. 703-738.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J. (1990B), "Positive Feedback Investment Strategies and Destabilizing Rational Speculation", Journal of Finance, 1990, 45(2), pp. 379-395.

Deel, R., The strategic electronic day trader, John Wiley & Sons, New York, 2000.

European Commission, First interim report on oil price developments and measure to mitigate the impact of increased oil prices, 2008, September, ECFIN/REP 54538, -Brussels.

Fama, E. F., "Efficient Capital Markets: A Review of Theory and Empirical Work", The Journal of Finance, 1970, 25(2), pp. 383-417.

Fattouh, B., "The Origins and Evolution of the Current International Oil Pricing System: A Critical Assessment". In R. Mabro (ed.) Oil in the Twenty-First Century: Issues, Challenges, and Opportunities. Oxford: Oxford University Press, 2006.

Financial Times, "Speculators caught short by crude price", June 9, 2008

Fattouh, B., OPEC Pricing Power, The Need for a New Perspective, Oxford Institute for Energy Studies, WPM 31, March 2007.

Frankel, J. A., "The Effect of Monetary Policy on Real Commodity Prices." In Campell, J. Y., Asset Prices and Monetary Policy, University of Chicago Press, 2008.

Frankel, J. A., Froot, K. A., "Chartists, Fundamentalists, and Trading in the Foreign Exchange Market", AEA Papers and Proceedings, 1990, 80(2), pp. 181-185.

Friedman, M., "The Case for Flexible Exchange Rates", in Friedman, M., Essays in Positive Economics, Chicago, University of Chicago Press, 1953.

Frydman, R., Goldberg, M. D., Imperfect Knowledge Economics: Exchange Rates and Risk, Princeton University Press, Princeton, NJ, 2007.

Gehrig, T., Menkhoff, L. (2005A), "The Rise of Fund Managers in Foreign Exchange: Will Fundamentals Ultimately Dominate?", The World Economy, 2005, 28 (4), 519-541.

Gehrig, T., Menkhoff, L. (2005B), "Extended Evidence on the Use of Technical Analysis in Foreign Exchange", International Journal of Finance and Economics, 2005, forthcoming.

Gehrig, T., Menkhoff, L., "Extended evidence on the use of technical analysis in foreign exchange", International Journal of Finance and Economics, 2006, 11(4), 327-338.

Gehrig, T., Menkhoff, L., "The Use of Flow Analysis in Foreign Exchange: Exploratory Evidence", Journal of International Money and Finance, 2004, 23 (4), 573-594.

Gilbert, C. L. (2010A), Speculative Influences on Commodity Futures Prices 2006-2008, UNCTAD Discussion Papers No. 197, March 2010.

Gilbert, C. L. (2010B), How to understand high food prices, Journal of Agricultural Economics, 61(2), 398-425.

Gutierrez, L., Speculative bubbles in agricultural commodity markets, European Review of Agricultural Economics, June 2012.

Habermeier, K., Kirilenko, A. A., "Securities Transaction Taxes and Financial Markets", IMF Staff Papers, special issue, 2003, 50, pp. 165-180.

Hommes, C., "Heterogeneous Agent Models in Economics and Finance", in Judd, K. L., Tesfatsion, L. (eds.), Handbook of Computational Economics, Elsevier, 2006, II(23), pp. 1109-1186.

Hotelling, H., "The Economics of Exhaustible Resources". Journal of Political Economy, 1931, Vol. 39:137-175.

Huizinga, H., "A European VAT on financial services?", Economic Policy, October 2002, pp. 499-534.

Interagency Task Force on Commodity Markets (ITF), Interim Report on Crude Oil, Washington, D. C., July 2008 http://www.cftc.gov/stellent/groups/public/@newsroom/documents/file/itfinterimreportoncrudeoil0708.pdf

International Monetary Fund, Global Slowdown and Rising Inflation, World Economic Outlook Update, Washington, July 2008 (http://www.imf.org/external/pubs/ft/weo/2008/update/02/index.htm).

Irwin, S. H., Holt, B. R., "The Impact of Large Hedge Fund and CTA Trading on Futures Market Volatility" in Gregoriou, G. N., Karavas, V. N., L'Habitant, F. S., Rouah, F. (eds.), Commodity Trading Advisers: Risk, Performance Analysis and Selection, John Wiley & Sons, New York, 2004, 151-182.

Irwin, S. H., Sanders, D. R., The Impact of Index and Swap Funds on Commodity Futures Markets: Preliminary Results, OECD Food, Agriculture and Fisheries Working Papers, No. 27, 2010

Irwin, S. H., Sanders, D. R., New Evidence on the Impact of Index Funds in U.S. Grain Futures Markets, Canadian Journal of Agricultural Economics, 59(4), December 2011, 519–532.

Kaufman, P. J., The New Commodity Trading Systems and Methods, John Wiley and Sons, New York, 1987.

Keynes, J. M., The General of Employment, Interest and Money, MacMillan, London, 1936.

Krugman, P., "Fuels on the Hill", New York Times, June 27, 2008 (www.nytimes.com/2008/06/27/opinion/27krugman.html).

Levich, R., Thomas, L., "The Significance of Technical Trading Rule Profits in the Foreign Exchange Market: a Bootstrap Approach", Journal of International Money and Finance, 1993, 12, 451-474.

Lo, A. W., Mamaysky, H., Wang, J., Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation, Journal of Finance, 2000, 55 (4), 1705-1765.

Mayer, J., The Growing Interdependence between Financial and Commodity Markets, UNCTAD Discussion Papers, No. 195, October 2009.

Mabro, R., The International Oil Price Regime: Origins, Rationale, and Assessment. The Journal Of Energy Literature, XI(1), 2005.

Marshall, B. R., Cahan, R. H., Cahan, J. M., Can Commodity Futures Be Profitably Traded With Quantitative Market Timing Strategies?, Journal of Banking and Finance, 2008, 32, 1810-1819.

Menkhoff, L., Taylor, M.P.,: The obstinate passion of foreign exchange professionals: Technical analysis, Journal of Economic Literature, 2007, 45(4), 936-972.

Murphy, J. J., Technical Analysis of the Futures Markets, New York Institute of Finance, New York, 1986.

Neely, C. J., "Technical Analysis in the Foreign Exchange Market: A Layman's Guide", Federal Reserve Bank of St. Louis Review, September/October 1997, 23-38.

Neely, C. J., Weller, P. A., Ulrich, J. M., The Adaptive Market Hypothesis: Evidence from the Foreign Exchange Market, forthcoming in Journal of Financial and Quantitative Analysis, 2007.

Oberlechner, T., "Importance of Technical and Fundamental Analysis in the European Exchange Market", International Journal of Finance and Economics, 2001, 6 (1), 81-93.

Osler, C. L., "Support for Resistance: Technical Analysis and Intraday Exchange Rates", Economic Policy Review, Federal Reserve Bank of New York, October 2000, 53-68.

Park, C-H., Irwin, S. H., The Profitability of Technical Trading Rules in US Futures Markets: A Data Snooping Free Test, AgMAS Project Research Report 2005-04, University of Illinois at Urbana-Champaign, 2005.

Podkolzina , I. What Factors Affect Oil Market Behavior? Problems of Economic Transition, 52(1), May 2009, 6-23.

Schneyer, J., „Corrected: Commodity Traders: The trillion dollar club", article published online on October 28, 2011 at http://www.reuters.com/article/2011/10/28/us-commodities-houses-idUSTRE79R4S320111028

Schulmeister, S., An Essay on Exchange Rate Dynamics, Wissenschaftszentrum Berlin, Discussion Paper IIM/LMP 87-9, 1987.

Schulmeister, St., Aktienkursdynamik und Realkapitalbildung in den USA und Deutschland, WIFO, Wien, 2003,

Schulmeister, S., Purchasing Power Parities, Exchange Rates and International Price Competitiveness, WIFO-Studie mit Unterstützung des Jubiläumsfonds der Österreichischen Nationalbank, 2005.

Schulmeister, S., "The interaction between technical currency trading and exchange rate fluctuations", Finance Research Letters, 2, 2006, pp. 212-233.

Schulmeister, St. (2007A), The Interaction between the Aggregate Behavior of Technical Trading Systems and Stock Price Dynamics, WIFO Working Paper, 2007, (http://stephan.schulmeister.wifo.ac.at/).

Schulmeister, St. (2007B), Die manisch-depressiven Schwankungen spekulativer Preise – Wie macht das die "unsichtbare Hand"?, WSI-Mitteilungen, 2007, 12, pp. 657-663.

Schulmeister, S. (2008A), "Components of the Profitability of Technical Currency Trading", Applied Financial Economics, 2008, 1-14.

Schulmeister, S. (2008B), "On the 'manic-depressive' fluctuations of speculative prices" in Hein, E., Niechoj, T., Spahn, P., Truger, A. (eds.), Finance-led Capitalism, Metropolis-Verlag, Marburg, 2008.

Schulmeister, S., (2009A), Trading Practices and Price Dynamics in Commodity Markets and the Stabilizing Effects of a Transactions Tax, Study of the Austrian Institute of Economic Research (WIFO), Vienna, January 2009.

Schulmeister, S. (2009B), Aggregate Trading Behavior of Technical Models and the Yen/Dollar Exchange Rate 1976-2007, Japan and the World Economy, 21(3), 270-279.

Schulmeister, S. (2009C), The Profitability of Technical Stock Trading: Has it Moved from Daily to Intraday Data? Review of Financial Economics, 18(4), October 2009, 163-210.

Schulmeister, S., Boom-Bust Cycles and Trading Practices in Asset Markets, the Real Economy and the Effects of a Financial Transactions Tax, WIFO Working Paper 364, March 2010.

Schulmeister, S., Schratzenstaller, M., Picek, O., A General Financial Transaction Tax – Motives, Revenues, Feasibility and Effects, Study of the Austrian Institute of Economic Research (WIFO) commissioned by Ökosoziales Forum Österreich and co-financed by the Ministry of Finance and the Ministry of Economics and Labour, Vienna, April 2008, (http://www.wifo.ac.at/wwa/jsp/index.jsp?fid=23923&id=31819&typeid=8&display_mode=2).

Sullivan, R., Timmermann, A., White, H., "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap", The Journal of Finance, 1999, 54(5), 1647-1693.

The Economist, Recoil, May 31st, 2008.

United States Senate, Permanent Subcommittee on Investigations, The Role of Market Speculation in Rising Oil and Gas Prices: A Need to Put the Back on the Beat, Staff Report, June 27th, 2006.

Velez, O. L., Capra, G., Tools an tactics for the master day trader: battle-tested techniques for day, swing and position traders, McGraw-Hill, 2000.

Annex

Table 2b: Performance of technical trading systems in the corn futures market

Price series: Daily prices of the CBOT corn futures contract
Begin of trading: 01/03/2007
End of trading: 12/30/2008

Short-term moving average (MAS):	15
Long-term moving average (MAL):	60

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2007	l	0	382.0	0.00	0.00
02/12/2007	n	40	408.5	6.94	63.30
02/12/2007	l	0	419.5	0.00	63.30
03/23/2007	s	39	410.5	-2.15	22.14
04/10/2007	n	18	361.5	11.94	62.95
04/10/2007	s	0	371.8	0.00	62.95
06/11/2007	n	62	394.5	-6.12	24.35
06/11/2007	s	0	402.0	0.00	24.35
06/12/2007	l	1	404.5	-0.62	22.78
07/06/2007	s	24	347.0	-14.22	-8.39
09/20/2007	l	76	366.0	-5.48	-13.62
11/12/2007	n	53	379.5	3.69	-7.01
11/12/2007	l	0	395.5	0.00	-7.01
02/11/2008	n	91	498.0	25.92	17.98
02/11/2008	l	0	510.5	0.00	17.98
04/10/2008	n	59	610.0	19.49	31.05
04/10/2008	l	0	623.5	0.00	31.05
06/10/2008	n	61	667.0	6.98	32.30
06/10/2008	l	0	693.0	0.00	32.30
07/24/2008	s	44	597.0	-13.85	20.89
11/10/2008	n	109	384.5	35.59	36.72
11/10/2008	s	0	402.5	0.00	36.72
12/30/2008	n	50	396.5	1.49	34.94

The profitability of the trading system

Gross rate of return per year	34.94
Net rate of return per year	34.80
Number of positions per year	
Long	4.02
Short	3.01
Neutral	0.00
Average duration of positions	
Long	51.38
Short	52.67
Neutral	0.00
Sum of profits per year	56.25
Profitable positions	
Number per year (NPP)	4.02
Average return	
Per position (RPP)	14.00
Per day (DRP)	0.233
Average duration (DPP)	60.12
Sum of losses per year	-21.30
Unprofitable positions	
Number per year (NPL)	3.01
Average return	
Per position (RPL)	-7.07
Per day (DRL)	-0.172
Average duration (DPL)	41.00

Table 2c: Performance of technical trading systems in the wheat futures market

Price series: Daily prices of the CBOT wheat futures contract
Begin of trading: 01/03/2007
End of trading: 12/30/2008

Short-term moving average (MAS):	15
Long-term moving average (MAL):	60

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2007	s	0	486.0	0.00	0.00
02/12/2007	n	40	462.0	4.94	45.06
02/12/2007	s	0	476.0	0.00	45.06
04/10/2007	n	57	455.0	4.41	35.18
04/10/2007	s	0	465.0	0.00	35.18
04/25/2007	l	15	503.0	-8.17	3.84
06/11/2007	n	47	545.0	8.35	21.87
06/11/2007	l	0	556.0	0.00	21.87
08/10/2007	n	60	668.0	20.14	49.45
08/10/2007	l	0	685.0	0.00	49.45
11/05/2007	s	87	775.0	13.14	51.06
11/12/2007	n	7	754.0	2.71	53.08
11/12/2007	s	0	774.0	0.00	53.08
12/11/2007	l	29	933.0	-20.54	26.66
02/11/2008	n	62	1153.0	23.58	43.87
02/11/2008	l	0	1155.0	0.00	43.87
04/07/2008	s	56	975.0	-15.58	26.16
04/10/2008	n	3	950.0	2.56	28.02
04/10/2008	s	0	961.0	0.00	28.02
06/10/2008	n	61	797.0	17.07	36.64
06/10/2008	s	0	813.0	0.00	36.64
06/25/2008	l	15	890.0	-9.47	29.21
07/22/2008	s	27	793.5	-10.84	20.82
08/11/2008	n	20	762.0	3.97	22.58
08/11/2008	s	0	790.0	0.00	22.58
11/10/2008	n	91	531.0	32.78	37.22
11/10/2008	s	0	550.0	0.00	37.22
12/30/2008	n	50	593.5	-7.91	30.69

The profitability of the trading system

Gross rate of return per year	30.69
Net rate of return per year	30.52
Number of positions per year	
Long	3.01
Short	5.52
Neutral	0.00
Average duration of positions	
Long	56.50
Short	35.27
Neutral	0.00
Sum of profits per year	67.10
Profitable positions	
Number per year (NPP)	5.52
Average return	
Per position (RPP)	12.15
Per day (DRP)	0.250
Average duration (DPP)	48.64
Sum of losses per year	-36.41
Unprofitable positions	
Number per year (NPL)	3.01
Average return	
Per position (RPL)	-12.09
Per day (DRL)	-0.378
Average duration (DPL)	32.00

Table 2d: Performance of technical trading systems in the rice futures market

Price series: Daily prices of the CBOT rice futures contract
Begin of trading: 01/03/2007
End of trading: 12/30/2008

Short-term moving average (MAS):	15
Long-term moving average (MAL):	60

The sequence of long, short and neutral positions

Date	Signal	Duration	Price	Single rate of return	Rate of return per year
01/03/2007	l	0	10.4	0.00	0.00
02/06/2007	s	34	10.1	-3.07	-32.91
02/12/2007	n	6	10.2	-0.99	-36.99
02/12/2007	s	0	10.5	0.00	-36.99
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
09/11/2007	l	32	11.3	-5.30	-31.62
10/10/2007	n	29	11.7	3.71	-23.50
10/10/2007	l	0	12.1	0.00	-23.50
12/10/2007	n	61	13.4	11.02	-7.51
12/10/2007	l	0	13.8	0.00	-7.51
02/11/2008	n	63	15.6	13.28	5.66
02/11/2008	l	0	15.9	0.00	5.66
04/10/2008	n	59	21.0	31.76	29.98
04/10/2008	l	0	21.4	0.00	29.98
05/29/2008	s	49	18.2	-15.35	16.17
06/10/2008	n	12	20.0	-10.19	8.70
06/10/2008	s	0	18.5	0.00	8.70
08/11/2008	n	62	16.2	12.27	15.42
08/11/2008	s	0	16.5	0.00	15.42
09/05/2008	l	25	18.9	-14.27	6.27
10/10/2008	n	35	16.6	-12.06	-0.89
10/10/2008	l	0	16.7	0.00	-0.89
10/15/2008	s	5	16.1	-3.59	-2.89
12/10/2008	n	56	14.1	12.55	3.81
12/10/2008	s	0	14.1	0.00	3.81
12/30/2008	n	20	15.6	-10.28	-1.46

The profitability of the trading system

Gross rate of return per year	-1.46
Net rate of return per year	-1.68
Number of positions per year	
Long	5.02
Short	6.02
Neutral	0.00
Average duration of positions	
Long	35.60
Short	30.92
Neutral	0.00
Sum of profits per year	45.78
Profitable positions	
Number per year (NPP)	4.02
Average return	
Per position (RPP)	11.40
Per day (DRP)	0.216
Average duration (DPP)	52.88
Sum of losses per year	-47.23
Unprofitable positions	
Number per year (NPL)	7.03
Average return	0.00
Per position (RPL)	-6.72
Per day (DRL)	-0.309
Average duration (DPL)	21.71

Table 3b: Pattern of corn futures contracts 1989 to 2008 (June)

Moving average models

Length i of MAS	1	1	5	10	15	15
Length i of MAL	30	30	35	40	45	60
Lag of signal execution		1				
Gross rate of return per year	0.20	2.45	0.98	3.35	5.35	9.13
Sum of profits per year	35.42	31.52	29.15	25.76	24.91	23.36
Profitable positions						
Number per year	5.38	3.60	3.24	2.80	2.22	1.78
Average return						
Per position	6.59	8.76	8.98	9.20	11.21	13.14
Per day	0.150	0.136	0.127	0.101	0.103	0.098
Average duration in days	43.87	64.25	70.73	90.92	109.08	134.18
Sum of losses per year	-35.22	-29.06	-28.17	-22.41	-19.56	-14.22
Unprofitable positions						
Number per year	20.58	9.64	7.87	4.49	3.96	2.71
Average return						
Per position	-1.71	-3.01	-3.58	-4.99	-4.95	-5.25
Per day	-0.273	-0.217	-0.208	-0.203	-0.160	-0.112
Average duration in days	6.27	13.87	17.23	24.60	31.00	46.66
Distribution of the single rates of return						
Mean	0.008	0.185	0.088	0.460	0.866	2.034
t-statistic	0.036	0.422	0.174	0.598	0.932	1.614
Median	-1.028	-1.842	-1.965	-2.009	-1.404	-1.259
Standard deviation	5.150	7.562	7.972	9.816	10.916	12.602
Skewness	3.882	2.851	2.313	1.933	1.853	1.694
Excess kurtosis	20.298	10.936	7.042	5.314	4.154	2.772
Sample size	584	298	250	164	139	101

Table 3c: Pattern of wheat futures contracts 1989 to 2008 (June)

Moving average models

Length i of MAS	1	1	5	10	15	15
Length i of MAL	30	30	35	40	45	60
Lag of signal execution		1				
Gross rate of return per year	2.64	3.94	4.01	2.78	0.59	2.84
Sum of profits per year	37.31	31.14	29.59	24.53	23.71	22.30
Profitable positions						
Number per year	6.09	3.96	3.24	2.40	2.04	1.91
Average return						
Per position	6.13	7.87	9.12	10.22	11.60	11.67
Per day	0.147	0.132	0.130	0.112	0.115	0.094
Average duration in days	41.72	59.48	70.27	91.26	101.15	123.95
Sum of losses per year	-34.67	-27.20	-25.58	-21.76	-23.11	-19.46
Unprofitable positions						
Number per year	18.71	8.93	7.24	4.62	4.36	3.51
Average return						
Per position	-1.85	-3.05	-3.53	-4.71	-5.31	-5.54
Per day	-0.312	-0.210	-0.187	-0.149	-0.146	-0.152
Average duration in days	5.93	14.52	18.91	31.59	36.33	36.49
Distribution of the single rates of return						
Mean	0.107	0.306	0.383	0.395	0.092	0.524
t-statistic	0.465	0.699	0.685	0.499	0.106	0.518
Median	-1.212	-1.669	-2.039	-2.398	-2.919	-2.515
Standard deviation	5.408	7.441	8.564	9.922	10.388	11.124
Skewness	4.265	3.096	2.477	1.898	1.835	1.678
Excess kurtosis	26.379	13.526	7.110	4.511	3.586	3.081
Sample size	558	290	236	158	144	122

Table 3d: Pattern of rice futures contracts 1989 to 2008 (June)

Moving average models

Length i of MAS	1	1	5	10	15	15
Length i of MAL	30	30	35	40	45	60
Lag of signal execution		1				
Gross rate of return per year	10.95	9.05	9.86	13.36	10.44	7.72
Sum of profits per year	40.19	35.93	32.06	30.96	28.12	25.39
Profitable positions						
Number per year	5.78	4.13	3.42	2.49	2.04	1.56
Average return						
Per position	6.96	8.69	9.37	12.44	13.76	16.32
Per day	0.150	0.140	0.124	0.127	0.116	0.111
Average duration in days	46.38	62.09	75.81	97.68	118.30	147.14
Sum of losses per year	-29.24	-26.88	-22.19	-17.60	-17.69	-17.66
Unprofitable positions						
Number per year	16.04	8.62	6.67	4.58	3.33	2.93
Average return						
Per position	-1.82	-3.12	-3.33	-3.84	-5.31	-6.02
Per day	-0.301	-0.248	-0.210	-0.144	-0.144	-0.130
Average duration in days	6.05	12.57	15.84	26.63	36.95	46.41
Distribution of the single rates of return						
Mean	0.502	0.709	0.978	1.891	1.941	1.721
t-statistic	1.606	1.312	1.453	1.990	1.480	1.136
Median	-1.066	-1.684	-1.724	-1.312	-1.779	-2.751
Standard deviation	6.919	9.141	10.114	11.944	14.359	15.150
Skewness	5.826	4.246	3.934	3.058	2.560	2.198
Excess kurtosis	48.216	25.654	21.190	12.616	8.444	6.049
Sample size	491	287	227	159	121	101

Table 4b: Pattern of corn futures contracts 1989 to 2008 (June)

Momentum models

Time span i	10	1	35	35	60	60
Lag of signal execution		10		1		1
Gross rate of return per year	-0.78	0.20	4.64	6.21	4.83	7.12
Sum of profits per year	41.42	33.89	31.10	26.86	27.82	24.42
Profitable positions						
Number per year	11.69	6.31	5.91	3.20	4.31	2.49
Average return						
Per position	3.54	5.37	5.26	8.40	6.45	-3.57
Per day	0.179	0.162	0.128	0.108	0.108	-0.164
Average duration in days	19.78	33.09	41.20	77.97	60.01	21.83
Sum of losses per year	-42.20	-33.69	-26.46	-20.66	-23.00	-17.30
Unprofitable positions						
Number per year	22.53	12.80	13.15	6.22	9.69	4.84
Average return						
Per position	-1.87	-2.63	-2.01	-3.32	-2.37	-3.57
Per day	-0.315	-0.216	-0.218	-0.179	-0.216	-0.164
Average duration in days	5.94	12.20	9.24	18.56	10.97	21.83
Distribution of the single rates of return						
Mean	-0.023	0.011	0.243	0.659	0.345	0.971
t-statistic	-0.148	0.039	0.889	1.108	0.741	1.144
Median	-0.723	-1.145	-0.821	-1.073	-0.913	-1.192
Standard deviation	4.286	5.632	5.658	8.635	8.246	10.868
Skewness	3.605	2.552	3.389	2.656	4.860	3.267
Excess kurtosis	22.921	11.510	16.335	9.624	28.470	12.909
Sample size	770	430	429	212	315	165

Table 4c: Pattern of wheat futures contracts 1989 to 2008 (June)

Momentum models

Time span i	10	1	35	35	60	60
Lag of signal execution		10		1		1
Gross rate of return per year	1.86	4.95	1.56	0.93	-0.36	1.65
Sum of profits per year	48.50	41.46	32.19	26.25	26.94	22.57
Profitable positions						
Number per year	11.69	7.20	6.36	3.11	5.24	2.98
Average return						
Per position	4.15	5.76	5.07	8.44	5.14	-3.89
Per day	0.206	0.180	0.134	0.121	0.103	-0.208
Average duration in days	20.14	32.05	37.85	69.93	49.84	18.70
Sum of losses per year	-46.64	-36.50	-30.63	-25.33	-27.29	-20.92
Unprofitable positions						
Number per year	21.64	12.27	12.49	7.11	10.84	5.38
Average return						
Per position	-2.15	-2.98	-2.45	-3.56	-2.52	-3.89
Per day	-0.360	-0.272	-0.246	-0.172	-0.263	-0.208
Average duration in days	5.99	10.95	9.96	20.74	9.56	18.70
Distribution of the single rates of return						
Mean	0.056	0.254	0.083	0.091	-0.022	0.198
t-statistic	0.330	0.879	0.259	0.165	-0.065	0.297
Median	-0.897	-1.245	-0.842	-1.470	-0.878	-1.472
Standard deviation	4.634	6.047	6.595	8.302	6.449	9.111
Skewness	2.999	2.293	3.768	2.468	3.870	3.070
Excess kurtosis	17.237	9.273	19.105	7.509	22.188	13.306
Sample size	750	438	424	230	362	188

Table 4d: Pattern of rice futures contracts 1989 to 2008 (June)

Momentum models

Time span i	10	1	35	35	60	60
Lag of signal execution		10		1		1
Gross rate of return per year	1.86	4.95	1.56	0.93	-0.36	1.65
Sum of profits per year	48.50	41.46	32.19	26.25	26.94	22.57
Profitable positions						
Number per year	11.69	7.20	6.36	3.11	5.24	2.98
Average return						
Per position	4.15	5.76	5.07	8.44	5.14	-3.89
Per day	0.206	0.180	0.134	0.121	0.103	-0.208
Average duration in days	20.14	32.05	37.85	69.93	49.84	18.70
Sum of losses per year	-46.64	-36.50	-30.63	-25.33	-27.29	-20.92
Unprofitable positions						
Number per year	21.64	12.27	12.49	7.11	10.84	5.38
Average return						
Per position	-2.15	-2.98	-2.45	-3.56	-2.52	-3.89
Per day	-0.360	-0.272	-0.246	-0.172	-0.263	-0.208
Average duration in days	5.99	10.95	9.96	20.74	9.56	18.70
Distribution of the single rates of return						
Mean	0.056	0.254	0.083	0.091	-0.022	0.198
t-statistic	0.330	0.879	0.259	0.165	-0.065	0.297
Median	-0.897	-1.245	-0.842	-1.470	-0.878	-1.472
Standard deviation	4.634	6.047	6.595	8.302	6.449	9.111
Skewness	2.999	2.293	3.768	2.468	3.870	3.070
Excess kurtosis	17.237	9.273	19.105	7.509	22.188	13.306
Sample size	750	438	424	230	362	188

Table 7b: Performance of technical trading systems by subperiods (ex post and ex ante)
Corn futures contract, daily data, 1989 to 2008 (June)

		All models	25 best models Ex post	25 best models Ex ante
1989-1992	Gross rate of return	-6.59	4.52	
	t-statistic	-0.835	0.575	
	DPP	71.64	74.90	
	Share of profitable models	6.0	100.0	
1993-1996	Gross rate of return	12.63	22.08	17.36
	t-statistic	0.913	1.401	1.060
	DPP	103.11	142.95	147.78
	Share of profitable models	99.8	100.0	100.0
1997-2000	Gross rate of return	3.45	13.78	-2.65
	t-statistic	0.319	1.253	-0.269
	DPP	75.08	58.96	84.76
	Share of profitable models	77.0	100.0	16.0
2001-2004	Gross rate of return	5.96	17.69	3.53
	t-statistic	0.444	1.241	0.287
	DPP	109.14	136.50	77.01
	Share of profitable models	87.7	100.0	76.0
2005-2008*)	Gross rate of return	3.50	21.10	15.21
	t-statistic	0.167	0.984	0.720
	DPP	81.16	93.87	92.14
	Share of profitable models	65.0	100.0	92.0
2008-2011**)	Gross rate of return	6.20	28.31	9.98
	t-statistic	0.258	1.096	0.427
	DPP	78.31	82.01	105.62
	Share of profitable models	72.8	100.0	88.0

*) January 2005 - June 2008. - **) July 2008 - June 2011.

Table 7c: Performance of technical trading systems by subperiods (ex post and ex ante)
Wheat futures contract, daily data, 1989 to 2008 (June)

		All models	25 best models Ex post	25 best models Ex ante
1989-1992	Gross rate of return	4.86	12.54	
	t-statistic	0.377	1.005	
	DPP	92.52	111.27	
	Share of profitable models	88.9	100.0	
1993-1996	Gross rate of return	7.05	17.80	6.34
	t-statistic	0.591	1.428	0.528
	DPP	89.07	66.14	92.20
	Share of profitable models	94.3	100.0	84.0
1997-2000	Gross rate of return	4.64	13.48	3.42
	t-statistic	0.393	1.187	0.293
	DPP	87.79	84.57	55.66
	Share of profitable models	82.7	100.0	72.0
2001-2004	Gross rate of return	-6.67	4.13	-8.97
	t-statistic	-0.552	0.321	-0.752
	DPP	88.05	63.79	78.95
	Share of profitable models	6.2	100.0	0.0
2005-2008*)	Gross rate of return	1.93	20.56	4.38
	t-statistic	0.093	1.034	0.225
	DPP	72.61	43.55	52.49
	Share of profitable models	60.9	100.0	64.0
2008-2011**)	Gross rate of return	-0.87	18.60	-2.17
	t-statistic	-0.058	0.853	-0.090
	DPP	67.52	47.55	47.86
	Share of profitable models	43.7	100.0	28.0

*) January 2005 - June 2008. - **) July 2008 - June 2011.

Table 7d: Performance of technical trading systems by subperiods (ex post and ex ante)
Rice futures contract, daily data, 1989 to 2008 (June)

		All models	25 best models Ex post	25 best models Ex ante
1989-1992	Gross rate of return	20.29	26.40	
	t-statistic	2.026	2.584	
	DPP	99.46	77.07	
	Share of profitable models	100.0	100.0	
1993-1996	Gross rate of return	28.83	39.45	31.11
	t-statistic	1.212	1.661	1.313
	DPP	83.15	68.82	67.54
	Share of profitable models	100.0	100.0	100.0
1997-2000	Gross rate of return	4.34	16.47	2.26
	t-statistic	0.231	1.008	0.090
	DPP	97.31	113.18	76.00
	Share of profitable models	74.0	100.0	72.0
2001-2004	Gross rate of return	11.47	25.05	5.95
	t-statistic	0.799	1.749	0.400
	DPP	85.19	76.19	89.71
	Share of profitable models	94.4	100.0	72.0
2005-2008*)	Gross rate of return	-3.93	7.69	-3.40
	t-statistic	-0.215	0.426	-0.174
	DPP	80.58	81.48	71.22
	Share of profitable models	29.2	100.0	20.0
2008-2011**)	Gross rate of return	2.98	23.14	1.94
	t-statistic	0.181	1.270	0.120
	DPP	71.11	37.34	78.98
	Share of profitable models	69.7	100.0	72.0

*) January 2005 - June 2008. - **) July 2008 - June 2011.

Table 8b: Distribution of trading systems by the gross rate of return and by the ratio of profit components over subperiods)

Corn futures contract, daily data, 1993 to 2008 (June)

Variable	Mean	S.D.	t-statistic
		All models N=5460	
Gross rate of return	6.35	7.23	
NPP/NPL	0.551	0.197	
DRP/DRL	0.659	0.246	
DPP/DPL	4.339	1.663	
		The 25 most profitable models: Ex post N=125	
Gross rate of return	20.59	5.14	30.324
NPP/NPL	0.825	0.187	16.116
DRP/DRL	0.818	0.372	4.766
DPP/DPL	4.376	1.957	0.211
		The 25 most profitable models: Ex ante	
Gross rate of return	8.68	8.91	2.912
NPP/NPL	0.605	0.160	3.710
DRP/DRL	0.691	0.345	1.020
DPP/DPL	4.293	2.185	-0.234

NPP (NPL). Number of profitable (unprofitable) positions per year.
DRP (DRL) Return per day during profitable (unprofitable) positions per year.
DPP (DPL) Average duration of profitable (unprofitable) positions.

The t-statistic tests for the significance of the difference between the mean of the four variables over the 125 cases of the best models (in and Ex ante) and the respective mean over the 5460 cases of all models

Table 8c: Distribution of trading systems by the gross rate of return and by the ratio of profit components over subperiods)

Wheat futures contract, daily data, 1993 to 2008 (June)

Variable	Mean	S.D.	t-statistic
		All models	
		N=5460	
Gross rate of return	1.22	7.70	
NPP/NPL	0.486	0.167	
DRP/DRL	0.734	0.249	
DPP/DPL	3.522	1.264	
		The 25 most profitable models: Ex post	
		N=125	
Gross rate of return	14.92	6.34	23.763
NPP/NPL	0.665	0.162	12.201
DRP/DRL	0.808	0.232	3.478
DPP/DPL	3.430	0.968	-1.046
		The 25 most profitable models: Ex ante	
Gross rate of return	0.60	9.08	-0.755
NPP/NPL	0.542	0.175	3.597
DRP/DRL	0.650	0.175	-5.247
DPP/DPL	3.233	0.654	-4.748

NPP (NPL). Number of profitable (unprofitable) positions per year.
DRP (DRL) Return per day during profitable (unprofitable) positions per year.
DPP (DPL) Average duration of profitable (unprofitable) positions.

The t-statistic tests for the significance of the difference between the mean of the four variables over the 125 cases of the best models (in and Ex ante) and the respective mean over the 5460 cases of all models

Table 8d: Distribution of trading systems by the gross rate of return and by the ratio of profit components over subperiods)
Rice futures contract, daily data, 1993 to 2008 (June)

Variable	Mean	S.D.	t-statistic
		All models	
		N=5460	
Gross rate of return	8.74	12.89	
NPP/NPL	0.589	0.231	
DRP/DRL	0.742	0.326	
DPP/DPL	4.033	1.635	
		The 25 most profitable models: Ex post	
		N=125	
Gross rate of return	22.36	10.73	13.959
NPP/NPL	0.878	0.317	10.122
DRP/DRL	0.919	0.372	5.265
DPP/DPL	3.628	1.346	-3.309
		The 25 most profitable models: Ex ante	
Gross rate of return	7.57	13.64	-0.949
NPP/NPL	0.597	0.200	0.440
DRP/DRL	0.728	0.284	-0.566
DPP/DPL	3.602	1.306	-3.629

NPP (NPL). Number of profitable (unprofitable) positions per year.
DRP (DRL) Return per day during profitable (unprofitable) positions per year.
DPP (DPL) Average duration of profitable (unprofitable) positions.

The t-statistic tests for the significance of the difference between the mean of the four variables over the 125 cases of the best models (in and Ex ante) and the respective mean over the 5460 cases of all models

Table 9b: Distribution of time by positions and transactions of technical trading systems
Moving average and momentum models
Corn futures contract, daily data, 1989 to 2008 (June)

Net position index	Share in total sample period in %	Mean of the net position index	Mean of the gross position index	
		Aggregate positions		
			Long	Short
> 90	27.91	98.57	99.28	-0.72
70 - 90	5.60	81.71	90.85	-9.15
50 - 70	3.97	60.26	80.13	-19.87
30 - 50	3.27	40.55	70.27	-29.73
30 - 10	2.88	19.55	59.78	-40.22
-10 - 10	2.93	-0.19	49.90	-50.10
-30 - -10	3.02	-20.50	39.75	-60.25
-50 - -30	3.28	-40.49	29.75	-70.25
-70 - -50	4.36	-60.62	19.69	-80.31
-90 - -70	6.18	-81.47	9.27	-90.73
< -90	36.61	-98.61	0.70	-99.30
Total	100.00	-9.37	45.31	-54.69

Net transaction index	Share in total sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
		Aggregate Transactions		
			Long	Short
> 70	0.00	0.00	0.00	0.00
50 - 70	0.09	59.52	59.67	-0.15
30 - 50	1.52	35.95	36.49	-0.54
30 - 10	9.80	17.66	18.92	-1.26
-10 - 10	76.65	0.00	1.56	-1.56
-30 - -10	10.84	-17.97	1.20	-19.17
-50 - -30	1.06	-35.94	0.38	-36.32
-70 - -50	0.05	-52.81	1.16	-53.97
< -70	0.00	0.00	0.00	0.00
Total	100.00	-0.03	3.79	-3.82

Table 9c: Distribution of time by positions and transactions of technical trading systems
Moving average and momentum models
Wheat futures contract, daily data, 1989 to 2008 (June)

	Aggregate positions			
Net position index	Share in total sample period in %	Mean of the net position index	Mean of the gross position index	
			Long	Short
> 90	24.61	98.33	99.16	-0.84
70 - 90	5.53	81.08	90.54	-9.46
50 - 70	3.28	61.08	80.54	-19.46
30 - 50	2.77	39.76	69.88	-30.12
30 - 10	2.82	19.66	59.83	-40.17
-10 - 10	2.81	0.25	50.13	-49.87
-30 - -10	3.44	-20.16	39.92	-60.08
-50 - -30	3.35	-40.38	29.81	-70.19
-70 - -50	4.18	-60.90	19.55	-80.45
-90 - -70	8.30	-81.49	9.25	-90.75
< -90	38.91	-98.43	0.79	-99.21
Total	100.00	-17.31	41.35	-58.65

	Aggregate Transactions			
Net transaction index	Share in total sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
			Long	Short
> 70	0.00	0.00	0.00	0.00
50 - 70	0.11	57.20	57.30	-0.09
30 - 50	1.41	35.74	36.35	-0.61
30 - 10	10.38	18.00	19.06	-1.07
-10 - 10	75.75	-0.10	1.53	-1.63
-30 - -10	11.19	-17.63	1.13	-18.75
-50 - -30	1.15	-35.37	0.73	-36.10
-70 - -50	0.02	-63.37	0.00	-63.37
< -70	0.00	0.00	0.00	0.00
Total	100.00	-0.04	3.85	-3.88

Table 9d: Distribution of time by positions and transactions of technical trading systems
Moving average and momentum models
Rice futures contract, daily data, 1989 to 2008 (June)

Net position index	Share in total sample period in %	Mean of the net position index	Mean of the gross position index	
		Aggregate positions		
			Long	Short
> 90	25.37	98.56	99.28	-0.72
70 - 90	5.14	80.90	90.45	-9.55
50 - 70	3.84	60.48	80.24	-19.76
30 - 50	2.71	40.02	70.01	-29.99
30 - 10	2.63	19.90	59.95	-40.05
-10 - 10	2.71	-0.11	49.94	-50.06
-30 - -10	3.43	-20.10	39.95	-60.05
-50 - -30	3.70	-40.34	29.83	-70.17
-70 - -50	4.51	-60.59	19.71	-80.29
-90 - -70	6.88	-81.53	9.23	-90.77
< -90	39.09	-98.68	0.66	-99.34
Total	100.00	-16.00	42.00	-58.00

Net transaction index	Share in total sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
		Aggregate Transactions		
			Long	Short
> 70	0.00	0.00	0.00	0.00
50 - 70	0.04	53.21	54.21	-1.01
30 - 50	1.15	35.68	36.64	-0.96
30 - 10	9.58	17.43	18.45	-1.02
-10 - 10	78.52	-0.03	1.52	-1.55
-30 - -10	9.57	-17.35	1.09	-18.43
-50 - -30	1.13	-35.88	0.63	-36.50
-70 - -50	0.02	-62.27	0.00	-62.27
< -70	0.00	0.00	0.00	0.00
Total	100.00	0.00	3.52	-3.52

Table 10b: Similarity of different types of technical trading systems in holding open positions
Corn futures contract, daily data, 1989 to 2008 (June)

	Relative share of models holding the same - long or short - position		
	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	60.07	65.14	72.30
1.0 - <=2.0	63.97	69.83	78.75
> 2.0	-	-	-
By stability			
Stable models	68.21	74.19	80.32
Unstable models	55.76	62.31	69.41
By duration of profitable positions			
Short-term	48.10	56.84	67.50
Medium-term	64.13	70.19	75.82
Long-term	76.93	82.08	85.28
All models	48.76	57.55	71.81

Table 10c: Similarity of different types of technical trading systems in holding open positions
Wheat futures contract, daily data, 1989 to 2008 (June)

	Relative share of models holding the same - long or short - position		
	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	55.39	63.74	72.20
1.0 - <=2.0	62.79	72.25	83.51
> 2.0	-	-	-
By stability			
Stable models	65.08	72.94	78.66
Unstable models	54.26	62.33	71.37
By duration of profitable positions			
Short-term	44.13	51.88	63.65
Medium-term	64.96	72.25	78.27
Long-term	79.98	82.26	85.24
All models	55.39	63.51	71.90

Table 10d: Similarity of different types of technical trading systems in holding open positions
Rice futures contract, daily data, 1989 to 2008 (June)

	Relative share of models holding the same - long or short - position		
	97.50% (|PI| > 95)	95% (|PI| > 90)	90% (|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	55.59	55.59	61.81
1.0 - <=2.0	59.03	64.87	71.73
> 2.0	61.28	74.13	81.54
By stability			
Stable models	65.70	71.48	77.12
Unstable models	56.97	62.48	68.95
By duration of profitable positions			
Short-term	44.86	53.31	63.35
Medium-term	66.88	72.29	77.48
Long-term	79.44	81.84	85.54
All models	58.08	64.46	71.92

Table 11b: Aggregate trading signals and susequent corn futures price movements
Corn futures contract, daily data, 1989 to 2008 (June)

Corn futures contract, 1993 to 2012 (June)	Time span j of CCP	More than 12.5% (25%, 50%) of all models change open positions in the same direction within 3 (5,. 10) business days					
k	i	From short to long positions (condition 1L)			From long to short position (condition 1S)		
		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
25	-3	591	2.0256	16.7230	644	-1.7238	-16.1989
	5	591	-0.1632	-0.6276	644	0.1787	1.5799
	10	591	-0.2734	-0.6707	644	0.1023	1.0276
	20	591	-1.0361	-2.6825	644	0.0660	0.9366
	40	591	-1.1300	-1.5281	644	-1.7847	-3.5386
50	-5	420	3.2306	18.7961	487	-2.8319	-19.3827
	5	420	-0.2994	-1.3265	487	0.2725	1.8495
	10	420	-0.4532	-1.3306	487	0.2991	1.5943
	20	420	-1.2564	-2.9827	487	0.1059	0.9242
	40	420	-1.0301	-1.1007	487	-1.8101	-3.2458
100	-10	275	5.0048	20.4606	300	-4.6033	-19.6236
	5	275	-0.6329	-2.7020	300	0.4250	2.1431
	10	275	-0.8118	-2.3087	300	0.4595	1.6490
	20	275	-1.7999	-3.7242	300	0.3677	1.3012
	40	275	-1.1522	-1.0688	300	-1.6518	-2.4799
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1409	-0.0272	0.3660	1851	-0.2299	-1.7865
	10	1409	0.2268	2.3721	1851	-0.4124	-2.1766
	20	1409	1.0106	5.6379	1851	-0.6424	-2.3361
	40	1409	2.2110	7.8314	1851	-1.2168	-3.2226

The table presents the means of commodity price changes over i business days (CCP_{t+j}) under four different conditions.
Condition 1L (S) comprises all situations where more than 12.5% (25%, 50%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) business days. The moves are restricted to a range of the position index PI_t between 95 and –95.
Condition 2L (S) comprises all situations beyond this range. i.e., where more than 97.5% of all trading systems hold long (short) positions.
More formally these conditions are defined as follows:

Condition 1L (S):
$[PI_t - PI_{t-i}] > k \ (<- k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \ (\leq = 0) \cap [-95 \leq PI_t \leq 95]$
k......25, 50, 100
i........3, 5, 10
n.......0, 1, ... t_{i-1}

Condition 2L (S):
PI > 95 (< -95)

$CCP_{t+j} = 100 * [CP_{t+j} - CP_t] / CP_t$ for j........5, 10, 20, 40
$CCP_{t+j} = 100 * [CP_t - CP_{t+j}] / CP_t$ for j.......-3, -5, -10

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Table 11c: Aggregate trading signals and susequent corn futures price movements
Wheat futures contract, daily data, 1989 to 2008 (June)

Corn futures contract, 1993 to 2012 (June)	Time span j of CCP	More than 12.5% (25%, 50%) of all models change open positions in the same direction within 3 (5,. 10) business days					
k	i	From short to long positions (condition 1L)			From long to short position (condition 1S)		
		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
25	-3	464	1.1197	7.9620	494	-1.0022	-7.1935
	5	464	0.4242	2.8114	494	-0.4464	-1.8718
	10	464	0.6501	3.0303	494	-0.4478	-0.8356
	20	464	-0.0657	0.9110	494	-0.2244	0.7291
	40	464	-0.1868	1.3725	494	-2.4509	-3.3585
50	-5	370	2.0362	11.0174	412	-1.9436	-10.9884
	5	370	0.2476	1.7097	412	-0.2706	-0.7613
	10	370	0.4306	2.0579	412	-0.2209	0.0530
	20	370	-0.4001	0.1237	412	0.1120	1.5995
	40	370	-0.6005	0.5121	412	-2.2746	-2.7845
100	-10	234	3.8914	12.6332	253	-3.4587	-11.7737
	5	234	-0.2084	-0.3296	253	-0.0396	0.3171
	10	234	0.0216	0.6299	253	-0.1585	0.2089
	20	234	-0.4603	-0.0030	253	0.6174	2.4765
	40	234	0.2134	1.5543	253	-1.4742	-0.9953
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1686	-0.1028	0.1536	2177	-0.1934	-0.8073
	10	1686	-0.3260	-0.5581	2177	-0.2654	-0.2296
	20	1686	-0.5969	-0.6280	2177	-0.4953	-0.1939
	40	1686	-1.0024	-0.3750	2177	-0.5817	1.0743

The table presents the means of commodity price changes over i business days (CCP_{t+j}) under four different conditions.
Condition 1L (S) comprises all situations where more than 12.5% (25%, 50%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) business days. The moves are restricted to a range of the position index PI_t between 95 and –95.
Condition 2L (S) comprises all situations beyond this range. i.e., where more than 97.5% of all trading systems hold long (short) positions.
More formally these conditions are defined as follows:

Condition 1L (S):
$[PI_t - PI_{t-i}] > k\ (<- k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0\ (\leq = 0) \cap [-95 \leq PI_t \leq 95]$
k......25, 50, 100
i........3, 5, 10
n.......0, 1, ... t_{i-1}

Condition 2L (S):
PI > 95 (< -95)

$CCP_{t+j} = 100 * [CP_{t+j} - CP_t] / CP_t$ for j........5, 10, 20, 40
$CCP_{t+j} = 100 * [CP_t - CP_{t+j}] / CP_t$ for j.......-3, -5, -10

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Table 11d: Aggregate trading signals and susequent corn futures price movements
Rice futures contract, daily data, 1989 to 2008 (June)

Corn futures contract, 1993 to 2012 (June)	Time span j of CCP	More than 12.5% (25%, 50%) of all models change open positions in the same direction within 3 (5,. 10) business days					
k	i	From short to long positions (condition 1L)			From long to short position (condition 1S)		
		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
25	-3	465	0.3205	2.7313	494	-0.4413	-2.7109
	5	465	0.0911	0.9322	494	-0.3137	-1.2837
	10	465	0.5977	2.6335	494	-0.4537	-1.1140
	20	465	-0.3855	-0.0118	494	-0.4777	-0.2786
	40	465	-0.7211	-0.0265	494	0.1341	1.3443
50	-5	370	0.4101	2.8289	412	-0.6912	-3.1491
	5	370	0.3118	1.8185	412	-0.2938	-1.0808
	10	370	0.8339	2.9897	412	-0.2855	-0.3343
	20	370	-0.2083	0.3216	412	-0.2410	0.3621
	40	370	-0.2166	0.6390	412	0.6632	1.9977
100	-10	234	0.5934	2.6551	253	-1.5119	-4.7334
	5	234	0.2002	1.2911	253	0.2168	1.4443
	10	234	1.2246	2.9951	253	-0.0321	0.5487
	20	234	0.5543	1.3659	253	-0.2251	0.3414
	40	234	1.1950	1.9266	253	1.9564	3.0570
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1687	0.1225	2.1611	2172	-0.3361	-2.6195
	10	1687	0.1342	2.2077	2172	-0.4807	-2.1847
	20	1687	0.1006	2.2473	2172	-0.7634	-2.0016
	40	1687	0.6139	4.2316	2172	-2.0363	-4.7389

The table presents the means of commodity price changes over i business days (CCP_{t+j}) under four different conditions.
Condition 1L (S) comprises all situations where more than 12.5% (25%, 50%) of all trading systems have been moving monotonically from short to long (long to short) positions over the past 3 (5, 10) business days. The moves are restricted to a range of the position index PI_t between 95 and –95.
Condition 2L (S) comprises all situations beyond this range. i.e., where more than 97.5% of all trading systems hold long (short) positions.
More formally these conditions are defined as follows:

Condition 1L (S):
$[PI_t - PI_{t-i}] > k\ (<- k) \cap [PI_{t-n} - PI_{t-n-1}] \geq 0\ (\leq = 0) \cap [-95 \leq PI_t \leq 95]$
k......25, 50, 100
i........3, 5, 10
n.......0, 1, ... t_{i-1}

Condition 2L (S):
PI > 95 (< -95)

$CCP_{t+j} = 100 * [CP_{t+j} - CP_t] / CP_t$ for j........5, 10, 20, 40
$CCP_{t+j} = 100 * [CP_t - CP_{t+j}] / CP_t$ for j.......-3, -5, -10

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Table 12b: Eight phases of technical trading and corn futures price movementss
Corn futures contract, daily data, 1989 to 2008 (June)

Conditions for CCPt + j	Time span j of CCPt + j	(Increasing) Long positions (Conditions .L.)			(Increasing) Short position (Conditions .S.)		
(= Phases of Technical trading)		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
1A	5	92	-0.3983	-1.0081	367	0.3098	1.8483
1B	5	328	-0.2716	-1.0149	120	0.1586	0.5759
2A	5	654	-0.5681	-3.2612	784	-0.5448	-3.5741
2B	5	755	0.4413	3.7340	1067	0.0014	0.6228
1A	10	92	-1.0577	-1.9599	367	0.3153	1.4379
1B	10	328	-0.2836	-0.5517	120	0.2495	0.7274
2A	10	654	-0.6766	-2.7105	784	-0.8389	-3.7141
2B	10	755	1.0094	5.6806	1067	-0.0990	0.2199
					0	0.0000	
1A	20	92	-2.0602	-2.6982	367	-0.0083	0.5674
1B	20	328	-1.0309	-2.0463	120	0.4549	1.8913
2A	20	654	-0.4238	-0.6553	784	-1.2598	-4.0860
2B	20	755	2.2532	8.2085	1067	-0.1888	0.2430
1A	40	92	-1.7908	-1.2949	367	-1.9256	-3.2382
1B	40	328	-0.8167	-0.6257	120	-1.4570	-1.0981
2A	40	654	0.4575	1.9017	784	-2.1719	-4.5496
2B	40	755	3.7299	9.3646	1067	-0.5151	-0.3653

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 50 and i = 5 (see Table 12a) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 25% of all trading systems have been moving from short to long (long to short) positions over the past five business days within the range $\{-95 \leq PI_t \leq 95\}$ and...

Condition 1L (S) A: Less than 50% of the models hold long (short) positions. i.e. $PI_t \leq 0$ ($PI_t \geq 0$).

Condition 1L (S) B: More than 50% of the models hold long (short) positions. i.e. $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 97.5% of all trading systems hold long (short) positions. i.e. $PI_t > 95$ ($PI_t < 95$).

Condition 2L (S) A: Comprises the first five business days for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other days for which condition 2L (S) holds true.

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Table 12c: Eight phases of technical trading and corn futures price movementss
Wheat futures contract, daily data, 1989 to 2008 (June)

Conditions for CCPt + j	Time span j of CCPt + j	(Increasing) Long positions (Conditions .L.)			(Increasing) Short position (Conditions .S.)		
(= Phases of Technical trading)		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
1A	5	91	0.4570	1.5335	312	-0.0604	0.2742
1B	5	279	0.1793	1.1775	100	-0.9263	-2.0004
2A	5	641	-0.0759	0.2614	715	0.0245	1.0449
2B	5	1045	-0.1193	0.0108	1462	-0.2999	-1.7329
1A	10	91	-0.0886	0.2586	312	-0.0491	0.5809
1B	10	279	0.6000	2.1836	100	-0.7568	-0.9187
2A	10	641	-0.5790	-1.5133	715	0.3045	2.6955
2B	10	1045	-0.1707	0.3179	1462	-0.5442	-2.0883
					0	0.0000	
1A	20	91	-0.8868	-0.4494	312	0.5077	2.4544
1B	20	279	-0.2414	0.4031	100	-1.1227	-1.6515
2A	20	641	-1.5766	-4.0200	715	0.3906	2.8643
2B	20	1045	0.0040	1.6022	1462	-0.9286	-2.1512
1A	40	91	-1.6232	-0.7297	312	-1.8559	-1.7673
1B	40	279	-0.2669	0.9398	100	-3.5810	-2.5132
2A	40	641	-1.4284	-1.3316	715	-0.3511	1.0445
2B	40	1045	-0.7411	0.3858	1462	-0.6945	0.6227

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 50 and i = 5 (see Table 12a) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 25% of all trading systems have been moving from short to long (long to short) positions over the past five business days within the range $\{-95 \leq PI_t \leq 95\}$ and...

Condition 1L (S) A: Less than 50% of the models hold long (short) positions. i.e. $PI_t \leq 0$ ($PI_t \geq 0$).

Condition 1L (S) B: More than 50% of the models hold long (short) positions. i.e. $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 97.5% of all trading systems hold long (short) positions. i.e. $PI_t > 95$ ($PI_t < 95$).

Condition 2L (S) A: Comprises the first five business days for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other days for which condition 2L (S) holds true.

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.

Table 12d: Eight phases of technical trading and corn futures price movementss
Rice futures contract, daily data, 1989 to 2008 (June)

Conditions for CCPt + j	Time span j of CCPt + j	(Increasing) Long positions (Conditions .L.)			(Increasing) Short position (Conditions .S.)		
(= Phases of Technical trading)		Number of cases	Mean of CCPt + j	t-statistic	Number of cases	Mean of CCPt + j	t-statistic
1A	5	91	-0.3514	-0.6429	312	-0.0074	0.4834
1B	5	279	0.5281	2.3111	100	-1.1873	-3.7175
2A	5	642	0.1130	1.4468	718	-0.4561	-2.7562
2B	5	1045	0.1284	1.7659	1454	-0.2768	-1.6309
1A	10	91	-0.0390	0.3248	312	-0.2099	-0.0222
1B	10	279	1.1186	3.1119	100	-0.5214	-0.7421
2A	10	642	0.2596	1.9469	718	-0.3906	-0.9395
2B	10	1045	0.0571	1.4198	1454	-0.5251	-2.1142
					0	0.0000	
1A	20	91	-1.4011	-1.1091	312	-0.3379	0.0939
1B	20	279	0.1808	0.8826	100	0.0611	1.0971
2A	20	642	-0.1999	0.5876	718	-0.1542	0.6945
2B	20	1045	0.2851	2.5009	1454	-1.0642	-3.2087
1A	40	91	-2.0052	-0.9274	312	1.1896	2.2680
1B	40	279	0.3667	1.1997	100	-0.9795	-0.2763
2A	40	642	-0.1697	1.2903	718	-0.7127	-0.0152
2B	40	1045	1.0954	4.5282	1454	-2.6899	-7.1409

Each of the four phases of technical trading defined by the conditions 1L (S) and the conditions 2L (S) for k = 50 and i = 5 (see Table 12a) is divided into two subphases by the conditions A and B:

Condition 1L (S): More than 25% of all trading systems have been moving from short to long (long to short) positions over the past five business days within the range $\{-95 \leq PI_t \leq 95\}$ and...

Condition 1L (S) A: Less than 50% of the models hold long (short) positions. i.e. $PI_t \leq 0$ ($PI_t \geq 0$).

Condition 1L (S) B: More than 50% of the models hold long (short) positions. i.e. $PI_t \geq 0$ ($PI_t \leq 0$).

Condition 2L (S): More than 97.5% of all trading systems hold long (short) positions. i.e. $PI_t > 95$ ($PI_t < 95$).

Condition 2L (S) A: Comprises the first five business days for which condition 2L (S) holds true.

Condition 2L (S) B: Comprises the other days for which condition 2L (S) holds true.

The t-statistic tests for the significance of the difference between the mean of the conditional commodity price changes and the unconditional mean over the entire sample.