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ÖSTERREICHISCHES INSTITUT FÜR WIRTSCHAFTSFORSCHUNG

Trading Practices and Price Dynamics in Commodity Markets and the Stabilising Effects of a Transaction Tax

Stephan Schulmeister

Research assistance: Eva Sokoll

January 2009

ÖSTERREICHISCHES INSTITUT FÜR WIRTSCHAFTSFORSCHUNG
AUSTRIAN INSTITUTE OF ECONOMIC RESEARCH

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Commissioned by the Federal Ministries of Finance and of Economics and Labour

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Abstract

Movements of commodity prices like the prices of crude oil, corn, wheat and rice are to a substantial extent lengthened and strengthened by speculation in the respective futures markets. In particular the widespread use of technical trading systems reinforces the trending behaviour of commodity prices. The impact of these trading practices on price overshooting was particularly pronounced during the recent commodity price boom. These conclusions can be derived from the performance of 1,092 trading systems in the futures markets for crude oil, corn, wheat and rice between 1989 and mid-2008 as well as from the impact of the aggregate trading behaviour of these models on the simultaneous and subsequent price movements. It is highly plausible that a financial transaction tax would dampen the volatility of commodity prices.

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Content

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Study commissioned by the Austrian Federal Ministry of Finance and the Austrian Federal Ministry of Economics and Labour

0. Executive Summary

The study documents the development of the most important determinants of commodity price dynamics according to two alternative explanations, the "fundamentalist hypothesis" and the "bull-bear-hypothesis".

The "fundamentalist hypothesis" assumes that commodity prices are determined exclusively by market fundamentals, i. e., by supply and demand conditions. Due to the predominance of rational market participants, destabilizing speculation can not distort commodities prices (and asset prices in general) in any systematic and/or persistent way.

The "bull-bear-hypothesis" holds that also (destabilizing) speculation exerts a substantial influence on commodity prices. By using trend-following trading techniques, speculators – in particular hedge funds, commodity index funds and investment banks - 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 2008. The main results are as follows.

The extent of the oil price boom since 2002, in particular the rise of oil prices from 52 $ to 147 $ between early 2007 and mid 2008, can hardly be accounted for by market fundamentals:

- Global oil inventories have risen substantially since 2002.
- The growth of global oil consumption has slowed down since 2005.
- The increase in oil demand originated exclusively from emerging market economies, demand of advanced economies has been stagnating.

- Even though net oil imports of China have been rising faster than global demand, they have been rising very continuously over the past 15 years. Moreover, China's net oil imports account for only 9% of global demand.
- The spectacular price boom over the first half of 2008 coincided with a continuous deterioration of the prospects for the global economy. At the same time, oil production picked up relative to demand.

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. Yet, over this period as well as over the subsequent two years, prices of corn, wheat and rice did not rise substantially. The price boom of these commodities took off only around mid 2007 when global production grew actually stronger than consumption (with the only exception of rice).

In particular the last phase of the price boom in the markets for corn, wheat and rice can hardly be explained by transactions of fundamentals-oriented (rational) commodity futures traders. During this phase, the monthly forecasts of the "World Agricultural Outlook Board" of the U.S. Department of Agriculture pointed to a rise of global supply relative to demand and, hence, to rising inventories. Yet, the respective futures prices continued to boom.

Trading volume of commodity derivatives contracts rose only moderately between 2000 and 2005, but has been tripling since then. The boom in trading activities was particularly strong between the 2nd quarter of 2007 and the 1st quarter of 2008. It does seem rather implausible that a fundamentals-oriented price discovery process should have called for such a strong increase in trading activities all of a sudden. Hence, this increase might be due to rising destabilizing speculation based on a general commodity "bull market" and carried out by the use of 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 1989/2008 (June) the models produce an annual gross return of 12.7%, 3.8%, 2.4%, and 12.6% when trading oil, corn, wheat and rice futures contracts, respectively.
- During the recent commodity price boom (January 2007 to June 2008), the profitability of technical trading in commodity futures markets was exceptionally high: More than half of the models produce an annual rate of return higher than 20%.
- As leveraged returns are roughly 15 times higher in commodity futures markets than the (unleveraged) returns, the profits one could have made through technical commodity

speculation were huge. Hence, they might have caused a rising number of financial investors to trade commodity futures.

- 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.

If one puts the results of this study in the context of other developments in recent years, then the following picture emerges. This picture sketches the interaction between fundamental factors and non-fundamental (speculative) factors in the process of commodity price formation:

- Prospects of tightening conditions in several commodity markets 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) caused market participants to expect rising commodity prices.
- Based on these fundamentals-oriented, "bullish" expectations, financial investors put additional funds into commodity derivatives. These funds are estimated to have risen from 13 bill. $ to roughly 260 bill. $ between 2003 and mid 2008.
- The additional demand stemming from hedge funds, commodity index funds and investment banks drove commodity futures prices up. These price movements spilled over to the spot markets since futures prices are used as benchmarks in contracts concerning the delivery of physical commodities.
- Based on the "bullishness" in commodity derivatives markets, short-term oriented speculators reacted much stronger to news in line with the expectation of rising prices than to news which contradicted the "market mood". Hence, they put more money into long positions than into short positions and held long positions longer than short positions. Due to this trading behavior, upward commodity price runs lasted longer in recent years than downward runs causing 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.

- After the outbreak of the financial crisis in mid 2007 hedge funds, index funds and investment banks put additional money into commodities derivatives in order to compensate for the losses incurred by the credit crisis and the related fall in stock prices.
- In addition to that, also the dollar depreciation contributed to the acceleration of the commodity price boom between mid 2007 and mid 2008.
- The interaction of all these forces caused overall commodities prices to rise by roughly 120% between early 2007 and mid 2008 (according to the S&P GSCI index).
- Around mid 2008 the "bull market" tilted into a "bear market": Within less than 4 months overall commodities prices have declined by almost 60%, thereby erasing the price rise which took place over the preceding 18 months. It seems highly probable that (technical) speculation, in particular on behalf of financial investors, has contributed to the extent and the speed of the recent fall of commodities prices.

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".

The present study confirms in detail the picture of asset price fluctuations in general as sketched in a study on the feasibility of a general financial transaction tax (FTT): Not only commodity prices, but also exchange rates and stock prices move in a sequence of runs which accumulate to long-term upward and downward trends ("bull markets" and "bear markets"). The use of trend-following technical trading systems in derivatives markets contribute significantly to this pattern of asset price dynamics.

A general FTT would specifically reduce "excessive liquidity" stemming from very short-term oriented and destabilizing transactions. There are two reasons for this presumption. First, a FTT makes trading the more costly the shorter its time horizon is (e. g., technical trading based on intraday data). Second, a FTT will dampen specifically derivatives trading since the tax rate refers to contract value (e. g., the effective tax on the margin "invested" is by the leverage factor higher than the tax relative to the value of the transaction). For the same reasons, derivatives transactions for hedging purposes as well as "real-world-transactions" (spot) would hardly be affected by a low FTT between 0.1% and 0.01%.

The study estimates the revenues of a general FTT for 2007. If trading declines due to the introduction of a FTT according to the medium "transactions-reduction-scenario", overall tax revenues would have reached 1.685% of world GDP at a tax rate of 0.1%, and 0.529% at a tax rate of 0.01%. In absolute terms, overall revenues would have amounted to 287.3 bill. $ in 20007, even at the small tax rate of 0.01% in. More than half of the revenues (164.4 bill. $) would stem from derivatives transactions on exchanges (these transactions could be taxed most easily due to the use of electronic settlement systems).

1. Motivation, scope and structure of the study

The spectacular rise of commodity prices which took off in 2005 and which accelerated in 2007, as well as the collapse of commodity prices since mid 2008 call for a concrete explanation. Such an explanation is a prerequisite of a comprehensive diagnosis of the present state of the global economy for at least three reasons. First, the tripling of all important commodity prices popped up production costs, deteriorated expectations and, hence, has directly dampened economic growth, in particular since mid 2007 (in addition to the outbreak of the financial crisis). Second, rising commodity prices were the main cause of the acceleration of (headline) inflation which prevents central banks, notably the ECB, to loosen monetary policy in face of a marked economic slump. Third, the extent and the speed of the decline in commodities prices (by far exceeding their decline after 1929) will strongly dampen import demand of commodity producing countries and thereby deepen the recession in advanced economies.

In spite of the importance of the rise and fall 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 explanations of the first group share the assumption that commodity prices have been determined (almost) exclusively by market fundamentals, i. e., by supply and demand conditions. Due to the predominance of rational market participants, destabilizing speculation can not distort commodities prices (and asset prices in general) in any systematic and/or persistent way. I call this proposition the "fundamentalist hypothesis".

The second group of explanations holds that in addition to fundamental factors also (destabilizing) speculation has exerted a substantial influence on commodity prices in recent years. In particular hedge funds, commodity index funds and investment banks have increasingly invested in commodity derivatives. By using trend-following trading techniques speculators have caused commodity prices to move in a sequence of long-term upward trends (bull markets) and downward trends (bear markets), overshooting their fundamental equilibrium in both directions. I call this proposition the "bull-bear-hypothesis".

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):

- 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.

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.

Moreover, it is sometimes argued by proponents of the "fundamentalist hypothesis" that speculation in oil futures markets "may raise the price of 'paper barrels', but not of the black stuff refiners turn into petrol" (The Economist, 2008). Also the well-known economist Paul Krugman (Princeton University) argues that speculation in the futures markets cannot directly influence the (spot) price of physical oil because "buying a futures contract doesn't directly reduce the supply of oil to consumers" (Krugman, 2008). Hence, Krugman shares with other prominent economists (like Jeffrey Frankel from Harvard University) the opinion "that the usual telltale signs of a speculative price boom are missing". [1])

This opinion got support from prominent politicians like the US Treasury Secretary Hank Paulson: "I don't believe financial investors are responsible to any significant degree for this priced movement" (referring to the oil price). "Financial investors …..don't set trends, they follow the trends." (Financial Times, 2008).

Proponents of the "bull-bear-hypothesis" hold that asset prices are not only driven by fundamentals, but also by destabilizing speculation.[2]) This hypothesis is based on several observations and their interpretation:

- Even though the fundamental factors mentioned above will have contributed to rising commodity prices, they did not change that markedly over the past 3 years as to explain the extent of the price boom.

[1]) The weblog of Jeff Frankel is to be found at http://content.ksg.harvard.edu/blog/jeff_frankels_weblog/.

[2]) This proposition has been elaborated already in 2006 in a report of the U. S. Senate Subcommittee on Investigations (U. S. Senate, 2006). For a recent paper see Davidson (2008).

- 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 were 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).
- Over the last 3 years trading volume of commodity futures and options on exchanges has tripled, 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.
- The combined value of outstanding commodity derivatives contracts on US exchanges (4.8 trillion $) and in the global over-the-counter (OTC) markets (9.0 trillion $) is roughly 5 times higher than the volume of world trade of all non-manufactures (SITC0-4). This difference suggests that only a small part of derivatives trading stems from hedging "real-world-transactions".
- Revenues of the 10 largest investment banks generated from commodity derivatives trading in 2007 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). The greatest part of these profits will probably stem from the successful exploitation of commodity price trends.

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) caused 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.[3]) These funds are estimated to have risen from 13 bill. $ in 2003 to roughly 260 bill. $ in spring 2008.
- The additional demand stemming from hedge funds, commodity index funds and investment banks drove prices up in commodities futures markets. These price

[3]) As the financial investor George Soros put it in testimony before an U. S. Senate Committee on June 3, 2008: "The bubble is superimposed on an upward trends in oil prices that has a strong foundation in reality" (www.bloomberg.com on June 13, 2008).

movements spilled over to the spot markets since futures prices are used as benchmarks in contracts concerning the delivery of the physical commodities.[4])

- Based on the "bullishness" in commodity derivatives markets, short-term oriented speculators reacted much stronger to news in line with the expectation of rising prices than to news which contradicted the "market mood". Hence, they put more money into long positions than into short positions and held long positions longer than short positions. Due to this trading behavior, upward commodity price runs lasted longer in recent years 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 (the most popular technique of asset trading in general). 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.
- After the outbreak of the financial crisis in mid 2007 hedge funds, index funds and investment banks put additional money into commodities derivatives in order to compensate for the losses incurred by the credit crisis and the related fall in stock prices.
- The dollar depreciation also contributed to the acceleration of the commodity price boom since mid 2007.

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 and within such a short period of time (the outlook for the global economy has been deteriorating continuously already since the summer of 2007).

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 boom. 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 2008.

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,

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[4]) In the words of hedge fund manager Michael Masters when testifying before an U. S. Senate Committee in May 2008: "I don't know if you can classify it (i. e., the oil price rise) as a bubble or not. But there is no question that investor demand is having an effect on price. Very little of it has to do with physical supply and demand of crude oil." (www.bloomberg.com on June 13, 2008).

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:

- Summarize the most important theoretical assumptions underlying the "fundamentalist hypothesis" and the "bull-bear-hypothesis" (chapter 2).
- Sketch the development of daily futures prices of crude oil, corn, wheat and rough rice since 1989, in particular over the most recent boom between early 2007 and mid 2008. Examine whether long-term trends of rising (falling) prices (bull or bear markets) are brought about by short-term upward (downward) runs being steeper or lasting longer than counter-movements (chapter 3).
- Document the development of the most important indicators of supply and demand conditions in the spot markets of the four selected (physical) commodities (chapter 4).
- Compare this development to trading dynamics in the respective derivatives markets in order to gauge the relative weight of hedging and speculation in these markets (chapter 5).
- Document the profitability of 1092 popular technical trading systems in the futures markets of crude oil, corn, wheat and rice (chapter 6).
- 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 7).
- Discuss the (potential) stabilizing effects of a small tax on transactions in commodity derivatives markets (as part of a general and uniform financial transaction tax) and estimate the revenue potential of such a tax (chapter 8).

2. Theoretical and institutional aspects of commodity price formation

In this chapter I shall at first clarify the theoretical foundations of the "fundamentalist hypothesis" in general, i. e., the proposition that asset prices are determined by market fundamentals so that destabilizing speculation will influence prices at best over the very short run (if at all).[5]) In contrast to this proposition which still represents mainstream thinking in economics, I shall elaborate the assumptions underlying the "bull-bear-hypothesis". Then I discuss some theoretical aspects of commodity price formation which are due to the fact that theses goods serve also as a store of wealth (in particular if commodities are exhaustible). Next I clarify some institutional aspects of the "pricing system" in commodity markets, in particular the relationship between futures prices and spot prices. Finally, I describe the interaction between technical trading systems and futures price dynamics which represents an essential component of the "bull-bear-hypothesis".

[5]) The first part of this chapter draws heavily on chapter 2 in Schulmeister – Schratzenstaller – Picek, 2008.

The main assumptions and propositions underlying the "fundamentalist hypothesis" can be summarized as follows:

- Its theoretical benchmark model is an ideal, frictionless market where all participants are equipped with perfect knowledge and where no transaction costs exist. In this "world 0" there is no need for trading and, hence, for liquidity because prices would instantaneously jump to their new equilibrium in reaction to new information.
- The model underlying the "fundamentalist hypothesis" relaxes the assumptions of perfect knowledge and no transaction costs. Also in this "world" actors are fully rational and use the same information set and the same "true" model, but do not know the expectations of other actors. Hence, prices cannot reach a new equilibrium instantaneously but 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 equilibria.
- 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 asset prices smoothly and quickly to their equilibria (*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. As a consequence, speculation techniques based on past prices cannot be systematically profitable (otherwise a market cannot even be considered "weakly efficient" – Fama, 1970).

The "bull-bear-hypothesis" perceives trading behavior and price dynamics in asset markets as follows:

- Imperfect knowledge is a general condition of social interaction and, hence, is characteristic also for the market place. As a consequence, actors use different models and process different information sets when forming expectations and making decisions.[6])
- As human beings, actors' expectations and transactions are governed not only by rational calculations, but also by emotional und social factors (the latter two factors are

[6]) In a recent, pathbreaking book, *Frydman - Goldberg* (2007) demonstrate that recognizing the importance of imperfect knowledge is key to understanding outcomes in financial markets and that the difficulties encountered by neoclassical theory and behavioral finance models to explain financial market behaviour stem from their disregard of this insight.

particularly important in financial markets which are at times characterized by "manic" or "depressive" phases as the asset prices themselves).

- Not only are expectations heterogeneous but they are often formed only qualitatively, i. e., as regards the direction of a price movement. In financial markets, e. g., traders react to news by just forming qualitative expectations about the direction of the imminent price move (not only due to time pressure but also because one cannot know the expectations of other traders).
- Upward (downward) price movements – usually triggered by news - are lengthened by "cascades" of buy (sell) signals stemming from trend-following technical trading systems since "technical analysis" is the most widely used technique in short-term trading in financial markets.
- The "trending" behavior of short-term asset price movements (based on daily or intraday data) is fostered by the dominance of either a "bullish" or a "bearish" bias in expectations. News in line with the prevailing "market mood" gets higher recognition and reaction than news which contradict the "market mood". In addition, traders put more money into an open position and hold it longer if the current run is in line with the "bullish" or "bearish" sentiment than in the case of a run against the "market mood".
- In the aggregate, this behavior of market participants cause 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.
- Long-term price trends do not represent "bubbles", i.e., non-fundamental equilibrium paths, since market participants know in advance that any "bull market" and "bear market" will end, and that there will be significant counter-movements during the trend.

In order to clarify the theoretical differences between the "fundamentalist hypothesis" and the "bull-bear-hypothesis", it is useful to distinguish between three (theoretical) paths of asset prices, depending on the assumptions made about market conditions. "World 0" represents the case of an ideal, frictionless market where all participants are equipped with perfect knowledge and where no transaction costs exist (as usually assumed in theoretical models of asset pricing under rational expectations). In this world, prices would instantaneously jump to their new equilibrium in reaction to new information (*Habermeier – Kirilenko*, 2003). In "world I" all actors are also fully rational, but do not know the expectations of other participants. For that reason and also because transactions are costly, prices cannot jump instantaneously to the new equilibrium due to fundamental news but follow a gradual price discovery process towards the equilibrium. In "world II", there are also "bounded-rational" or even irrational traders who drive the price beyond its fundamental equilibrium.

A simple chart stylizes the three paths of asset prices over the short run (figure 1). In "world 0" new information at the point in time = 1 causes the asset price to jump instantaneously from the old equilibrium at P = 100 (at point A) to the new equilibrium at P = 104 (B). The price stays there until news in t = 3 cause the price to jump to P = 102 (E). Finally in t = 5 new information once again causes an instantaneous price adjustment to P = 106 (I).

In "world I" prices adjust only gradually, i.e., it takes a series of transactions to move the price from P = 100 to P = 104, i.e., from A to C. However, since there are only rational traders in this world, the price movement will stop at the new fundamental equilibrium level and stay there until t = 3 (then the price starts to move from D to F, and later from H to J).

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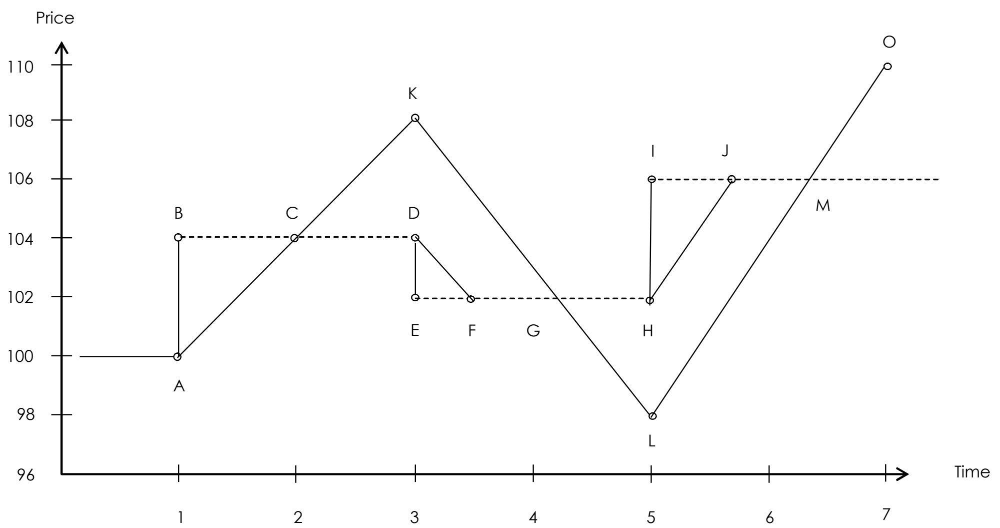
Figure 1: Three stylized paths of asset prices



In "world II" there exist traders who form their price expectations according to the most recent movements, i.e., when prices move persistently up (down) they expect the respective run or short-term trend to continue. Hence, they buy (sell) when prices are rising (falling), which in turn strengthens the trend.

As a consequence of this "trending", rational investors (in the sense of profit-seeking) will try to systematically exploit this non-randomness in price dynamics. As a consequence, the conditions of "world II" will 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 use of these strategies will in turn increase the momentum of price movements which will then hardly stop exactly at the new fundamental equilibrium (for models dealing with the interaction of heterogeneous actors see *DeLong et al.*, 1990A and 1990B; *Frenkel – Froot*, 1990; *De Grauwe – Grimaldi*, 2006; *Hommes*, 2006; *Frydman – Goldberg*, 2007).

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 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, 2008B).

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.

Since it is impossible to exactly prove one of the two hypotheses true and the other wrong I shall try to find empirical indicators which rather support 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, at least in part caused by technical speculation).

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).[7]) 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 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

[7]) 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.

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.
- In this sense, the oil price, driven up by speculation in the futures market, lies at the fundamental equilibrium level (the only difference to Frankel's model is, that in our case the increase in "underground inventories" is induced by higher futures prices instead of lower interest rates).
- 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.
- 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.

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.

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, 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."[8])

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."[9])

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 Europe, several major oil-producing countries such as Saudi Arabia, Kuwait and Iran rely on the IPE Brent Weighted Average (BWAVE)".[10])

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

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

[10]) 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,

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 "latecoming 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.

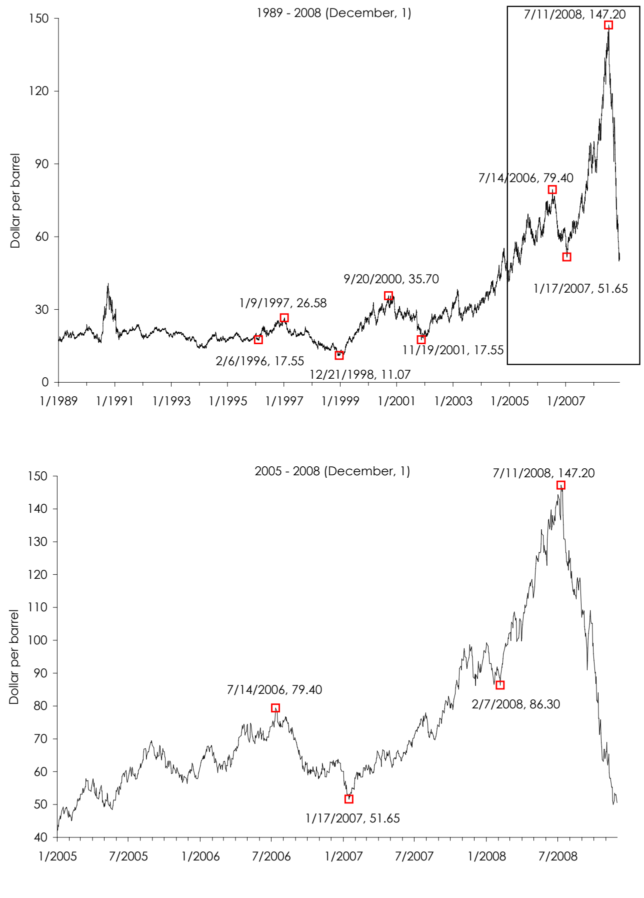
3. Some observations on the dynamics of commodity prices

Figures 2 and 3 show that daily commodity futures prices fluctuate strongly, however, most of the time they fluctuate around "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).

ICE is the leading market place for trading Brent oil futures as NYMEX is the leading exchange for trading WTI oil futures.

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 2). 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 2: Dynamics of oil futures prices
Daily price of the most traded WTI crude oil futures contract (NYMEX)

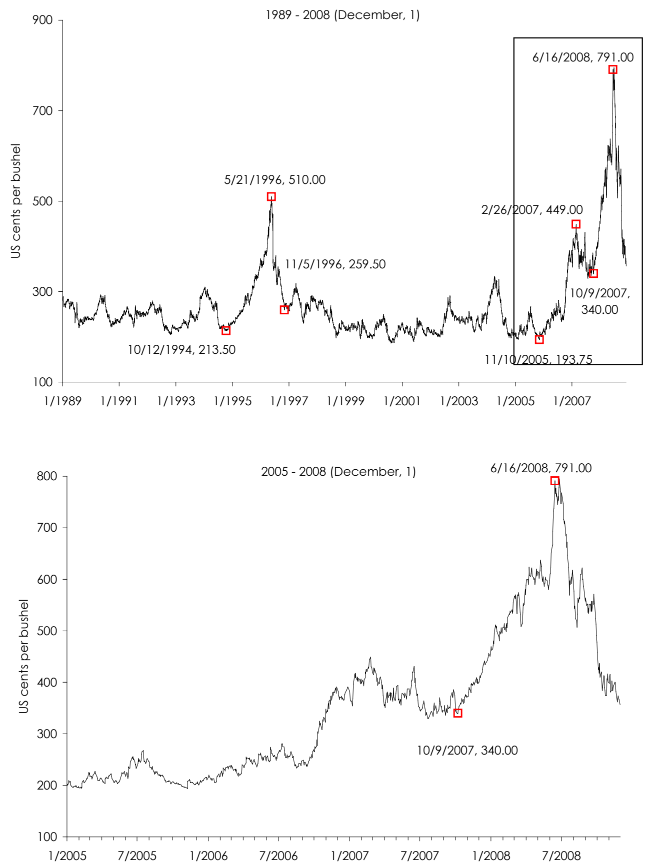


Source: New York Mercantile Exchange (NYMEX).

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 futures 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 2). 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 2).

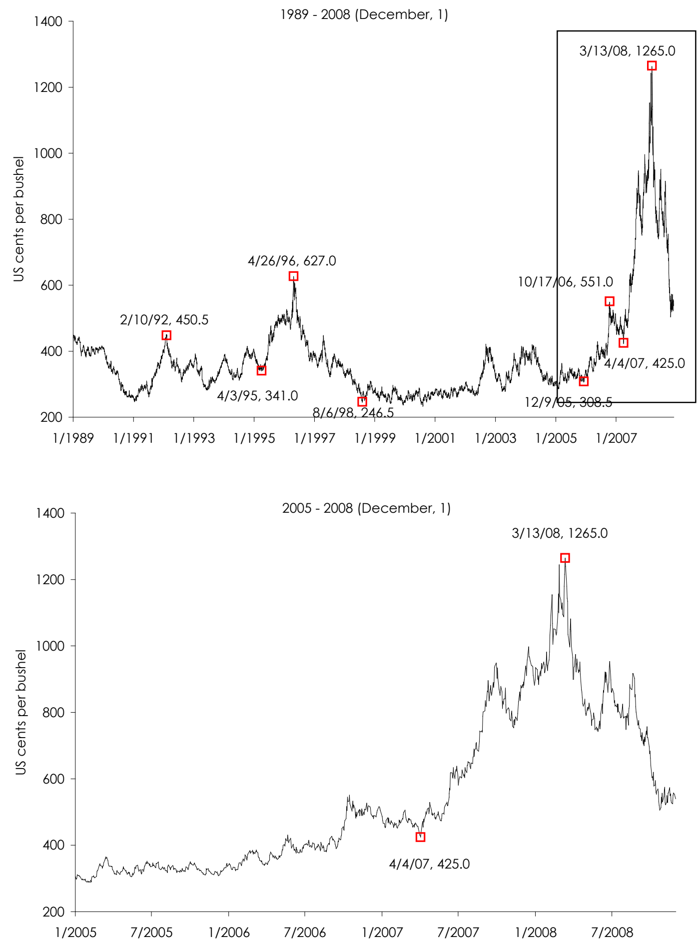
Figure 3: Dynamics of corn futures prices
Daily price of the most traded corn futures contract (CBOT)



Source: Chicago Board of Trade (CBOT)

Figures 3 to 5 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".

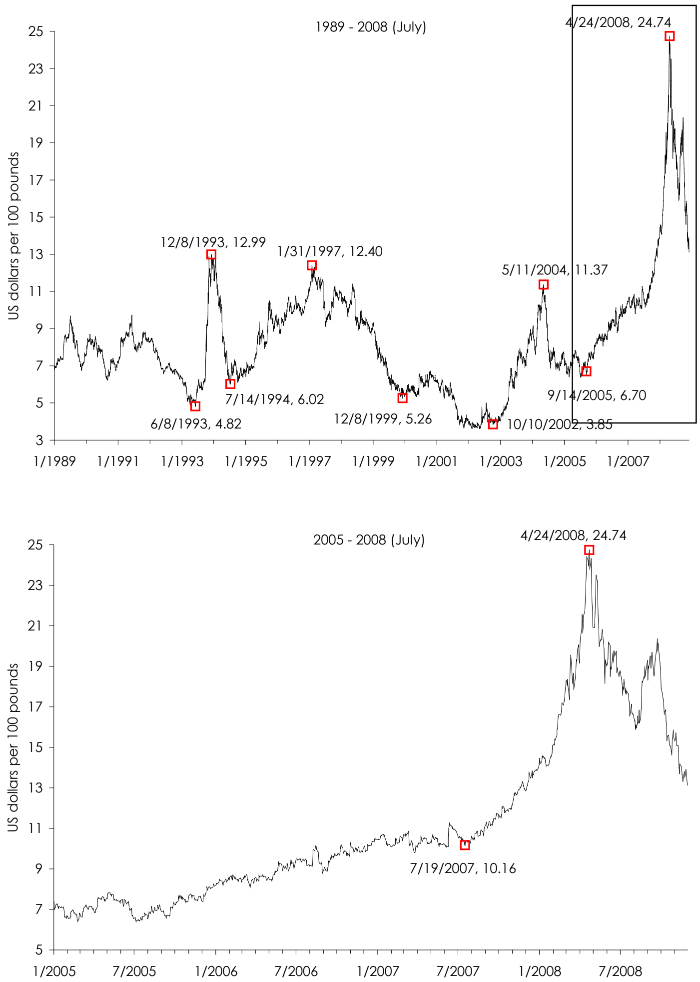
Figure 4: Dynamics of wheat futures prices
Daily price of the most traded wheat futures contract (CBOT)



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 2 to 5). A long-term upward (downward) trend ("bull market" 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 5: 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 15 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 2 to 5). 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 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 (2.29 days versus 1.73 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).

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 ¹)	Number	Average durations in days	Average slope ¹)
				Based on original data			
Oil	21/12/1998 - 09/20/2000	101	2.51	1.44	100	1.76	-1.43
	09/20/2000 - 11/19/2001	72	1.99	2.15	73	1.95	-2.68
	11/19/2001 - 07/14/2006	286	2.21	3.16	285	1.75	-3.51
	07/14/2006 - 01/17/2007	32	1.47	3.29	33	2.33	-3.75
	01/17/2007 - 07/11/2008	92	2.29	4.25	91	1.73	-3.90
Corn	10/12/1994 - 05/21/1996	101	2.08	1.18	100	1.67	-0.97
	05/21/1996 - 11/05/1996	29	1.69	2.16	30	2.13	-2.57
	11/10/2005 - 02/26/2007	81	1.90	0.50	80	1.98	-0.39
	02/26/2007 - 10/09/2007	39	1.95	0.60	40	1.93	-0.74
	10/09/2007 - 06/16/2008	45	2.20	0.69	44	1.59	-0.58
Wheat	04/03/1995 - 04/26/1996	68	2.15	3.76	67	1.66	-3.36
	04/26/1996 - 08/06/1998	143	1.72	2.80	144	2.16	-3.03
	12/09/2005 - 10/17/2006	48	2.31	0.62	47	2.04	-0.55
	10/17/2006 - 04/04/2007	26	1.62	0.82	27	2.52	-0.71
	04/04/2007 - 03/13/2008	59	2.08	1.64	58	1.86	-1.31
Rice	07/14/1994 - 01/31/1997	64	5.34	1.64	63	4.27	-1.68
	01/31/1997 - 12/08/1999	72	3.85	1.41	73	5.61	-1.53
	10/10/2002 - 05/11/2004	37	5.57	0.65	36	4.46	-0.45
	05/11/2004 - 09/14/2005	25	4.56	0.46	26	7.26	-0.54
	09/14/2005 - 04/24/2008	62	5.92	0.43	61	4.21	-0.30
				Based on 5 days moving average			
Oil	21/12/1998 - 09/20/2000	36	7.64	0.70	35	4.29	-0.56
	09/20/2000 - 11/19/2001	30	4.40	0.89	29	5.14	-1.19
	11/19/2001 - 07/14/2006	101	6.57	1.42	100	4.49	-1.56
	07/14/2006 - 01/17/2007	10	3.20	1.21	11	8.70	-1.81
	01/17/2007 - 07/11/2008	36	6.36	2.21	35	3.89	-1.65
Corn	10/12/1994 - 05/21/1996	43	5.91	0.48	42	2.90	-0.34
	05/21/1996 - 11/05/1996	7	4.29	1.03	8	8.56	-1.06
	11/10/2005 - 02/26/2007	33	5.27	0.21	32	4.03	-0.16
	02/26/2007 - 10/09/2007	19	3.68	0.22	20	3.90	-0.32
	10/09/2007 - 06/16/2008	19	6.21	0.31	18	2.61	-0.24
Wheat	04/03/1995 - 04/26/1996	29	5.38	1.70	28	3.36	-1.12
	04/26/1996 - 08/06/1998	52	3.83	1.04	53	6.38	-1.26
	12/09/2005 - 10/17/2006	13	8.69	0.32	12	7.42	-0.24
	10/17/2006 - 04/04/2007	16	2.75	0.22	17	3.65	-0.32
	04/04/2007 - 03/13/2008	25	5.64	0.64	24	3.82	-0.45
Rice	07/14/1994 - 01/31/1997	64	5.34	1.64	63	4.27	-1.68
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	09/14/2005 - 04/24/2008	62	5.92	0.43	61	4.21	-0.30

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

If one examines the pattern of accumulation of price runs for all cases comprised in table 1, it turns out that in only 3 out of 40 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).[11]) 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).

4. Supply and demand conditions in commodity spot markets

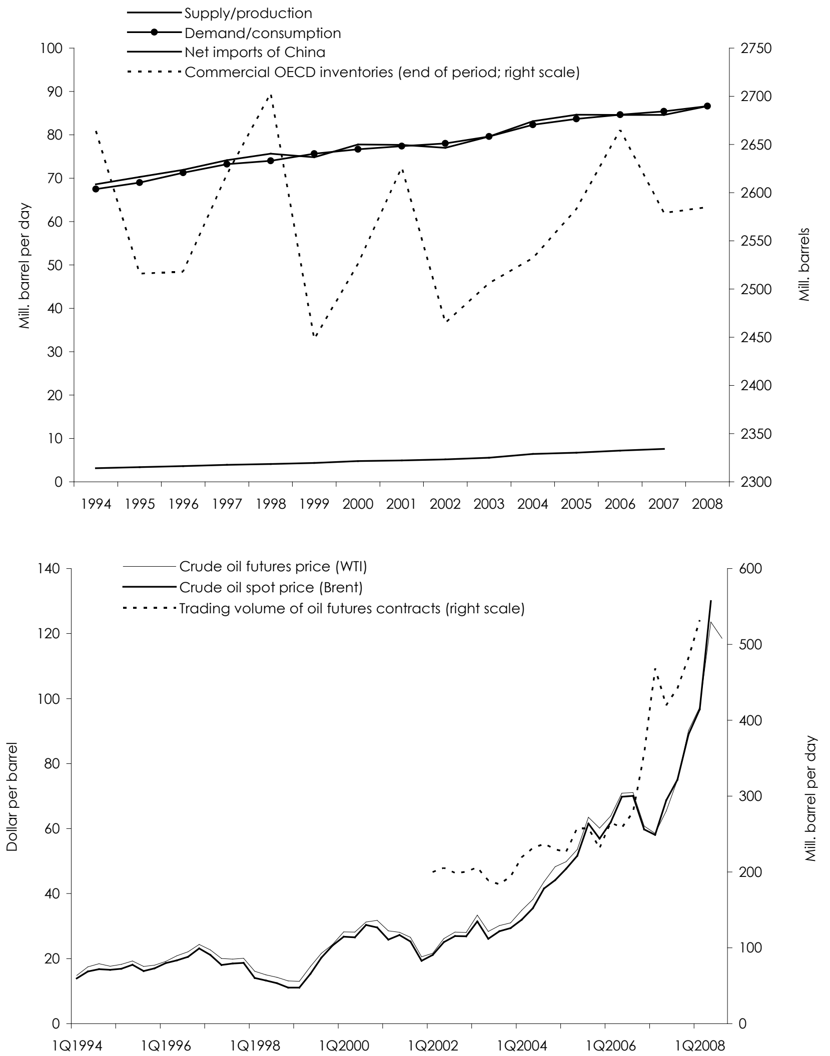
This section compares the development of supply of and demand for crude oil, corn, wheat and rice in the world spot markets and the related changes in inventories, to the movements of the respective futures prices.[12]) Such a comparison should help to evaluate the plausibility of the "fundamentalist hypothesis", namely, that futures prices reflect exclusively - at least primarily - the (expected) changes in market fundamentals.

Between 1994 and 2002 global supply (production) of crude oil rose by 1.5 % per year, slightly slower than global demand (+1.8 % - figure 6). 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).

11) 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, 2008D). 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.

12) 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.

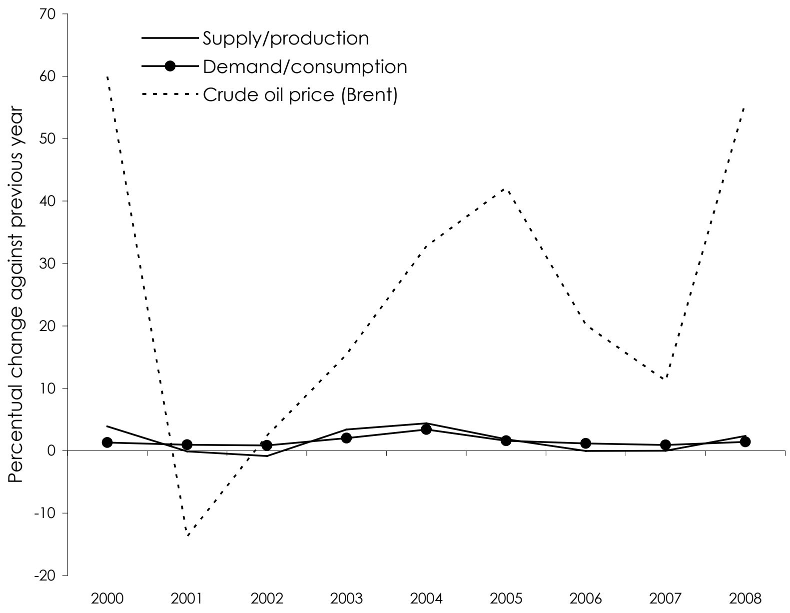
Figure 6: World market for crude oil, oil futures trading and oil price movements



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

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 6). In spite of this rise in (buffer) stocks, oil prices increased strongly between 2002 and 2006, namely, from 26.0 $ to 66.7 $.

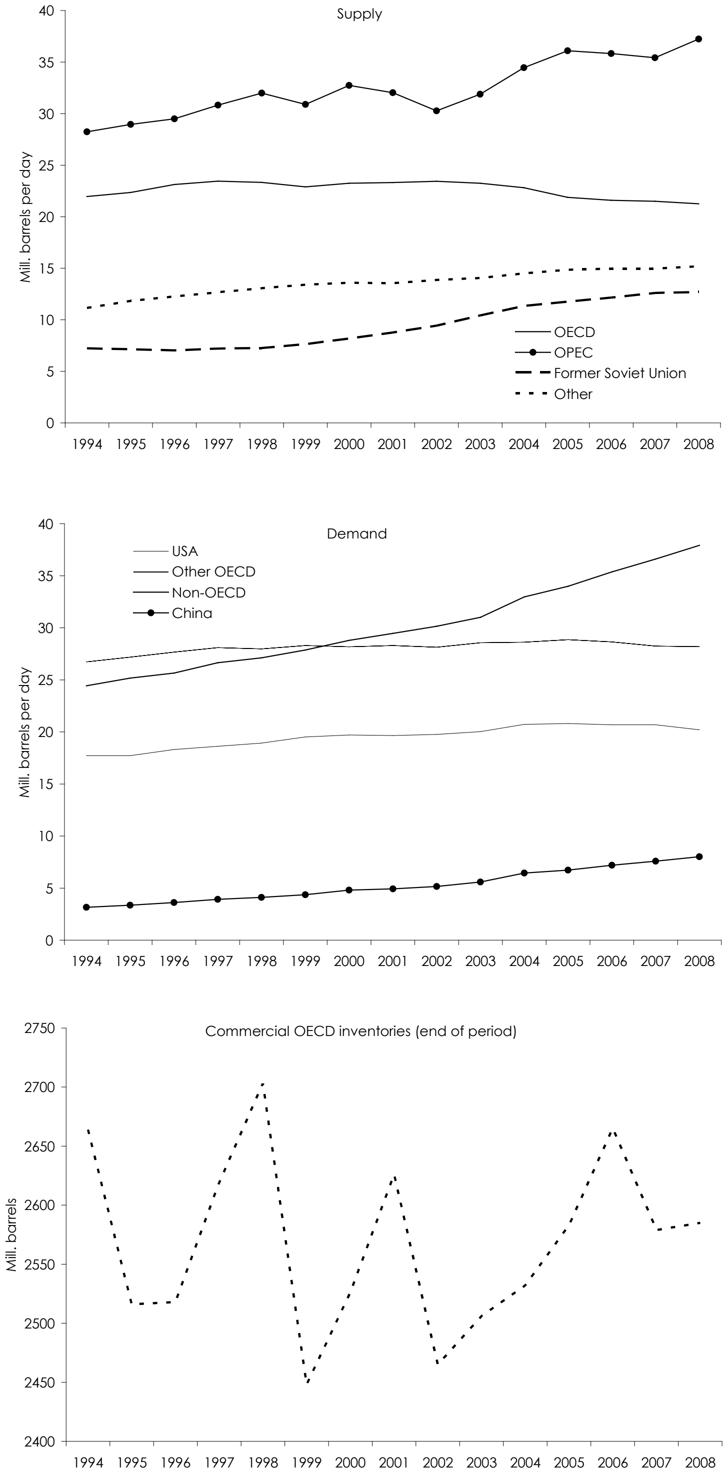
Figure 7: World market for crude oil



Source: Energy Information Agency (EIA), OECD.

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 2). This development can hardly be explained by the conditions in the market for physical crude oil. Even though 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 7), 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 6).

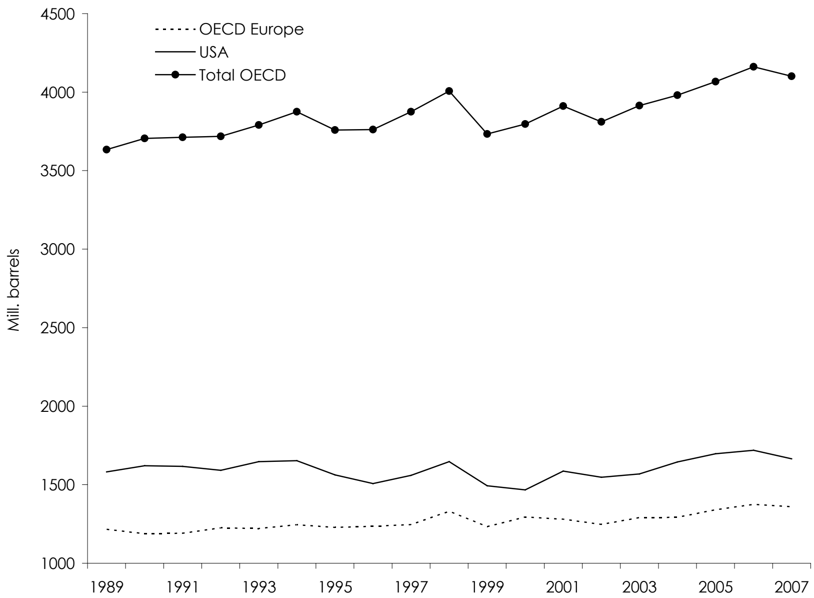
Figure 8: Global supply of and demand for crude oil



Source: Energy Information Agency (EIA).

The spectacular oil price boom over the first half of 2008 (futures prices climbed by 60 $ - figure 2) 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. It seems therefore hard to interpret this last phase of the oil price boom as primarily determined by market fundamentals.

Figure 9: Total crude oil inventories in OECD countries1)

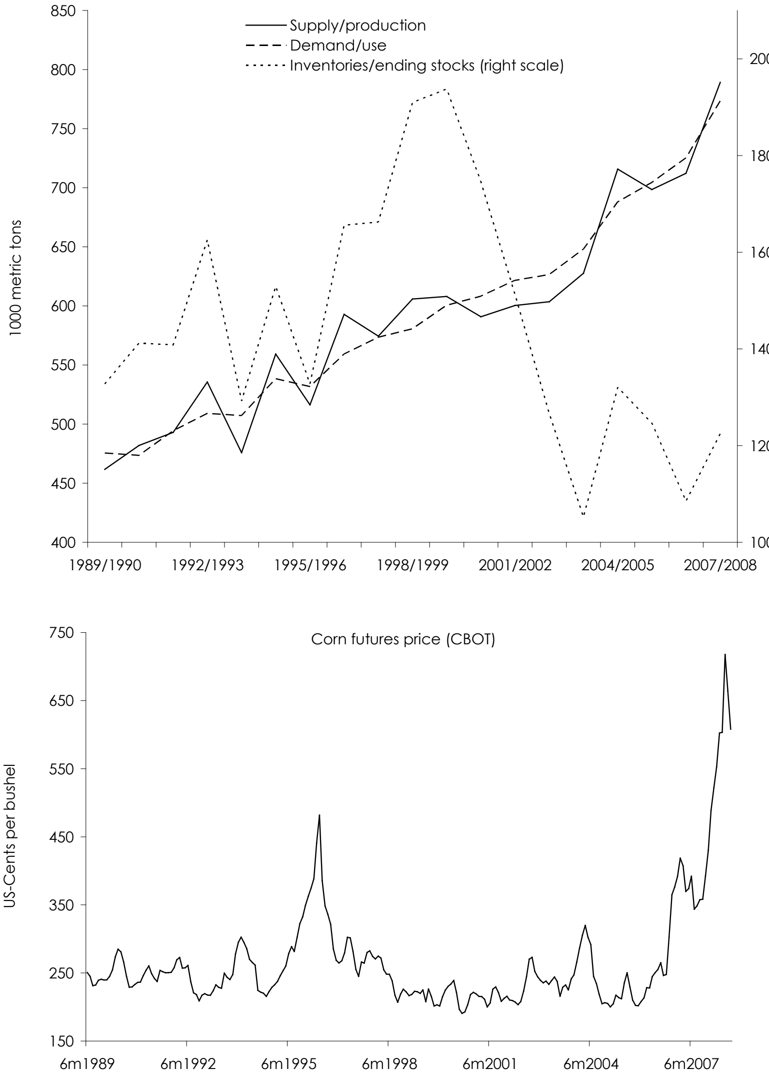


1) Including strategic reserves.
Source: Energy Information Agency (EIA).

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, net oil imports of China account for only 9% of global demand (2007 – China still produces roughly half of its oil consumption). Moreover, China's net oil imports have expanded very continuously over the past 15 years. Hence, oil demand from China can hardly explain the extent of the oil price boom of the last 5 years, in particular its acceleration between the beginning of 2007 and mid 2008 (figures 6 and 2).

Table 6 displays the (small) annual percentage changes of supply of and demand for crude oil on the one hand, and the (huge) 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 some doubts on the assessment that the oil price boom and its acceleration since 2007 can entirely be explained by market conditions.

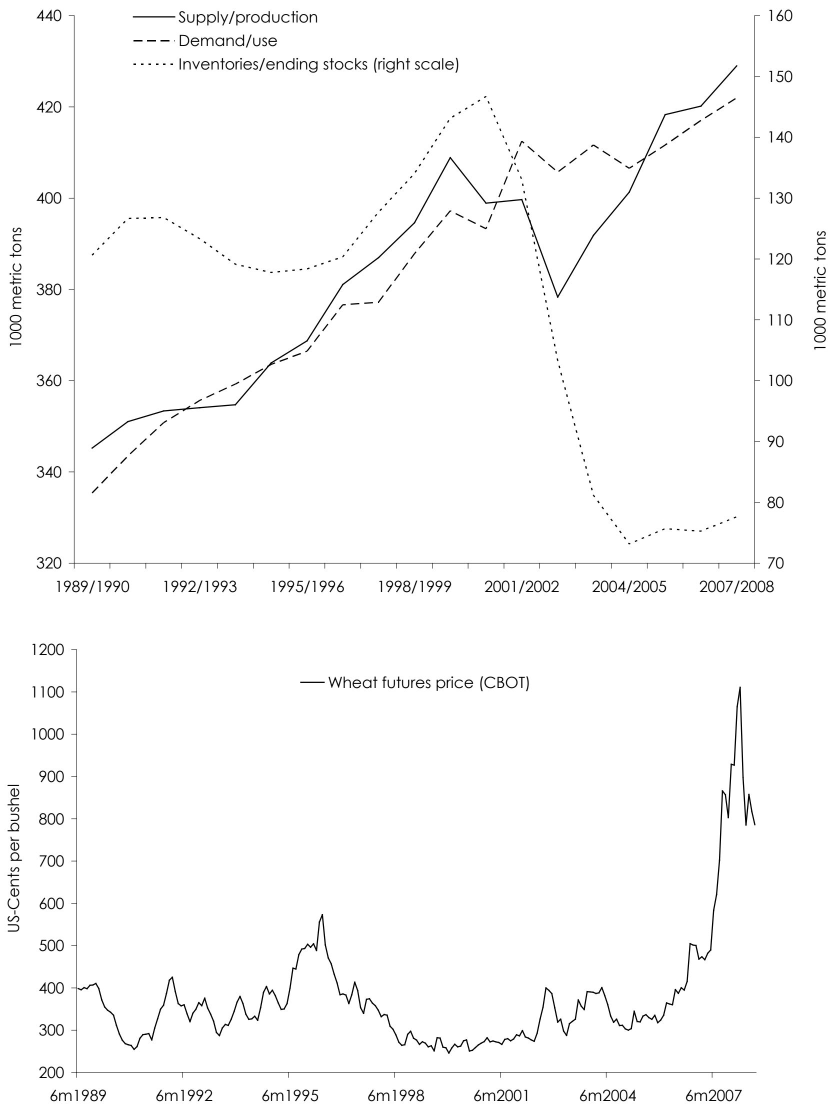
Figure 10: World market conditions for corn and corn futures price movements



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

Figure 9 shows global supply (production) of and demand (consumption) for crude oil by country groups. Since 2002 the increase in demand originated exclusively from emerging market economies, demand of advanced economies (OECD countries) has been stagnating. 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 commercial inventories rose. Including the strategic reserves, global inventories have increased already since 2002 by 290 mill. barrel (figure 9). One has to keep in mind, however, that building up inventories for strategic reasons increases demand and, hence, the upward pressure on prices.

Figure 11: World market conditions for wheat and wheat futures price movements



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

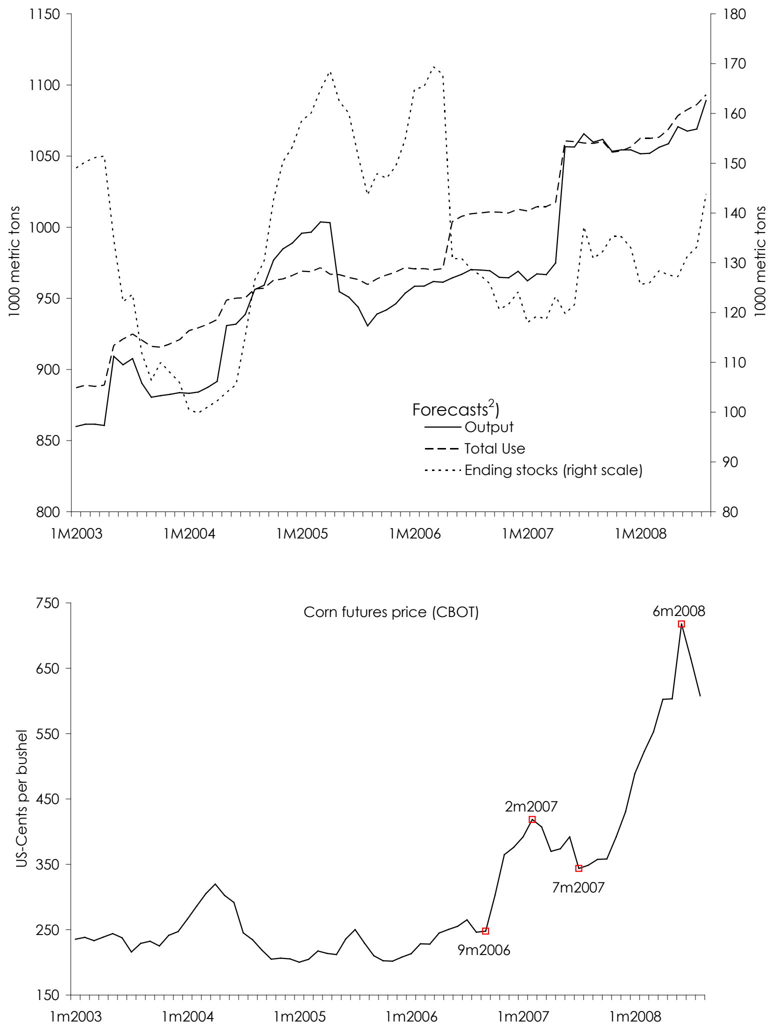
A comparison between supply and demand conditions in the spot markets for corn, wheat and rice on the one hand, and the development of the respective futures prices does also raise doubts about the relevance of the "fundamentalist hypothesis". Between the marketing periods 1999/2000 and 2003/2004, global 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 10 to 12). The price boom of these commodities took off only around mid 2007 (figures 3 to 5) 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).

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

S: 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 13 to 15 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).

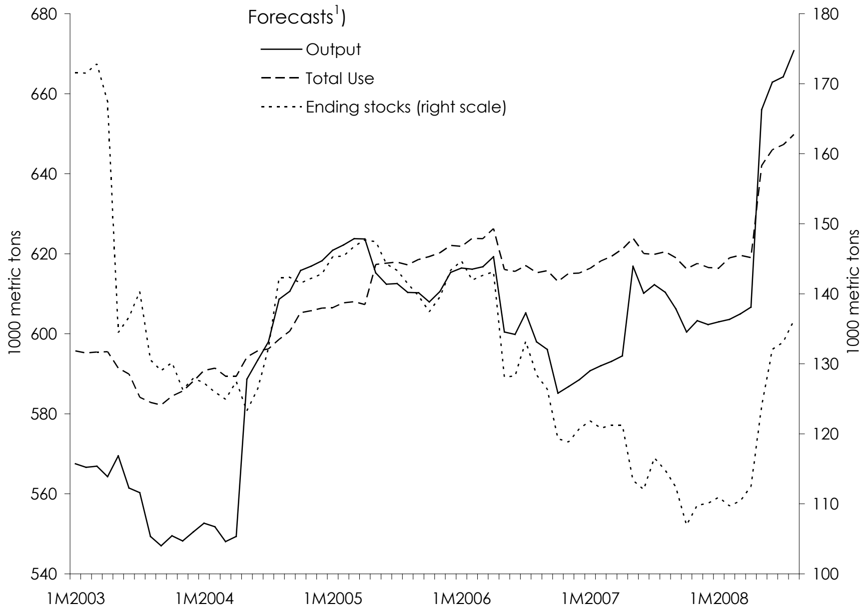
Figure 13: Forecasts of world market conditions for coarse grains1) and corn futures price movements

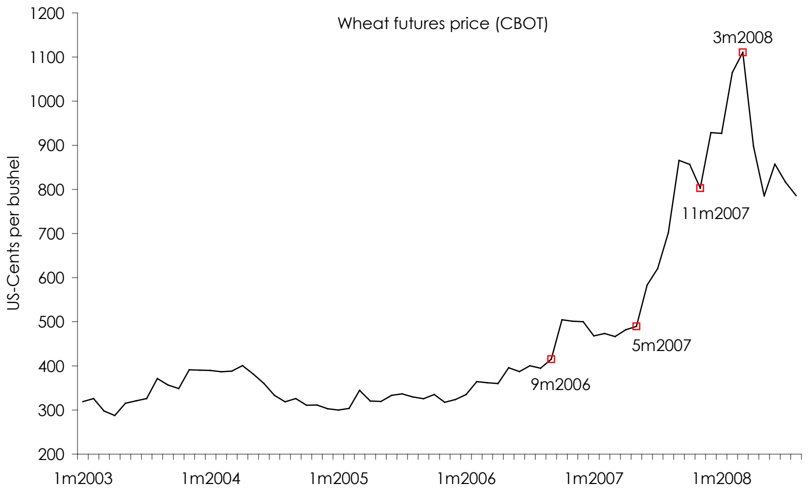


1) Primarily corn. 2) Monthly forecasts of market conditions in the current marketing year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

In early 2006, WASDE started to revise their forecast of coarse grain consumption upwards, and, hence, of inventories downwards. With some lag, corn futures prices picked up in September 2006 (figure 13). 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 in February 2008, corn futures prices kept booming until mid 2008 (figure 13).

Figure 14: Forecasts of market conditions for wheat and wheat futures price movements

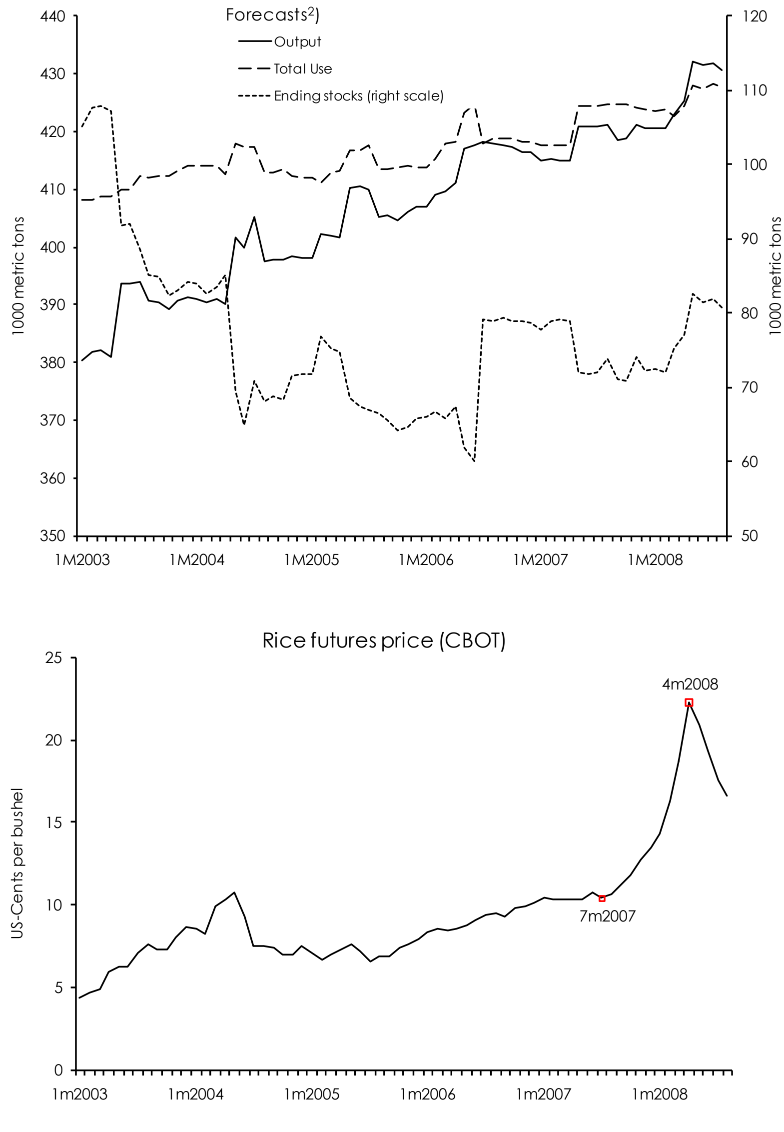




1) Monthly forecasts of market conditions in the marketing harvest year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

A comparison between WASDE projections for wheat and the development of wheat futures prices shows a similar picture (figure 14). 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 14).

Figure 15: Forecasts of market conditions for rice and rice futures price movements

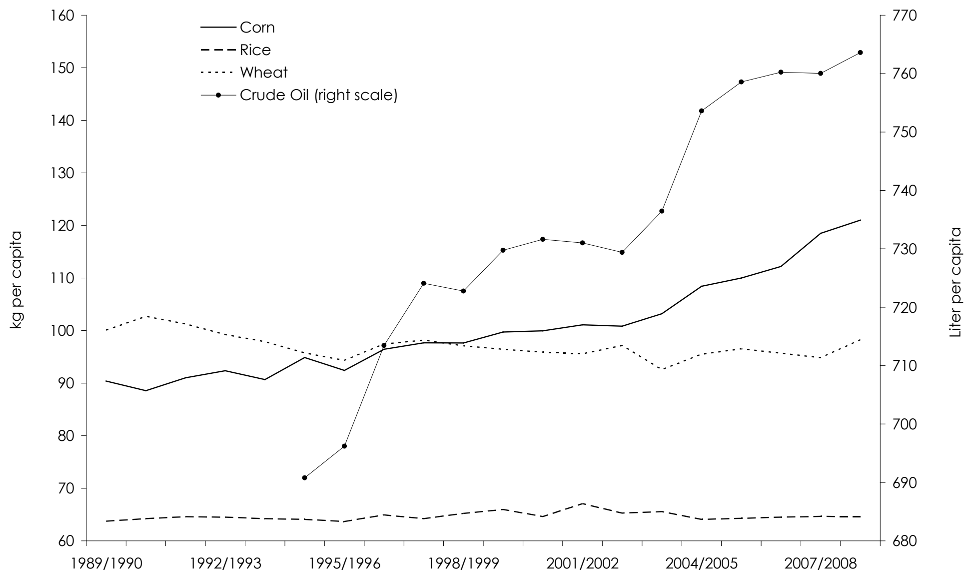


1) Monthly forecasts of market conditions in the marketing harvest year.
Source: U.S. Department of Agriculture - World Agricultural Supply and Demand Estimates (WASDE), CBOT.

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 24, 2008 (figures 5 and 15).

The presumption that commodities prices did overshoot their fundamental equilibrium (at least) during the last phase of the recent boom 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 have fallen by 64.0% from their recent peak, corn prices by 53.8%, wheat prices by 56.2%, and rice prices by 43.8% (until November 30, 2008).

Figure 16: World consumption of corn, rice and wheat per capita



S: U.S. Department of Agriculture.

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 16 shows a more differentiated picture. Per capita consumption of wheat and rice has remained stagnant over the past 20 years. Most probably 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. Crude oil consumption per capita rose strongly between 2003 and 2005, probably due to the high growth of the global economy. Since then, however, the increase in crude oil consumption has been slowing down considerably, suggesting that demand has adjusted to some extent to the higher price level.

The empirical evidence presented in the figures 6 to 16 lets one conclude that the change in the supply and demand conditions in the markets for physical crude oil, corn wheat and rice can hardly fully account for the extent of the boom in prices of these commodities. This presumption gets strong support from the decline of commodities prices since mid 2008. The extent of this decline – prices have fallen by roughly 60% over a period of four months – reflects at least in part the correction of a preceding overshooting. At the same time, the speed of the commodities price decline (faster than after 1929) suggests that short-term speculation based on an increasingly "bearish" market has exacerbated the downward trend.

The "bull-bears-hypothesis" as described in chapter 1 and concretized in chapter 2 taking the recent oil price boom as example, sketches an overall picture of trading behavior 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".

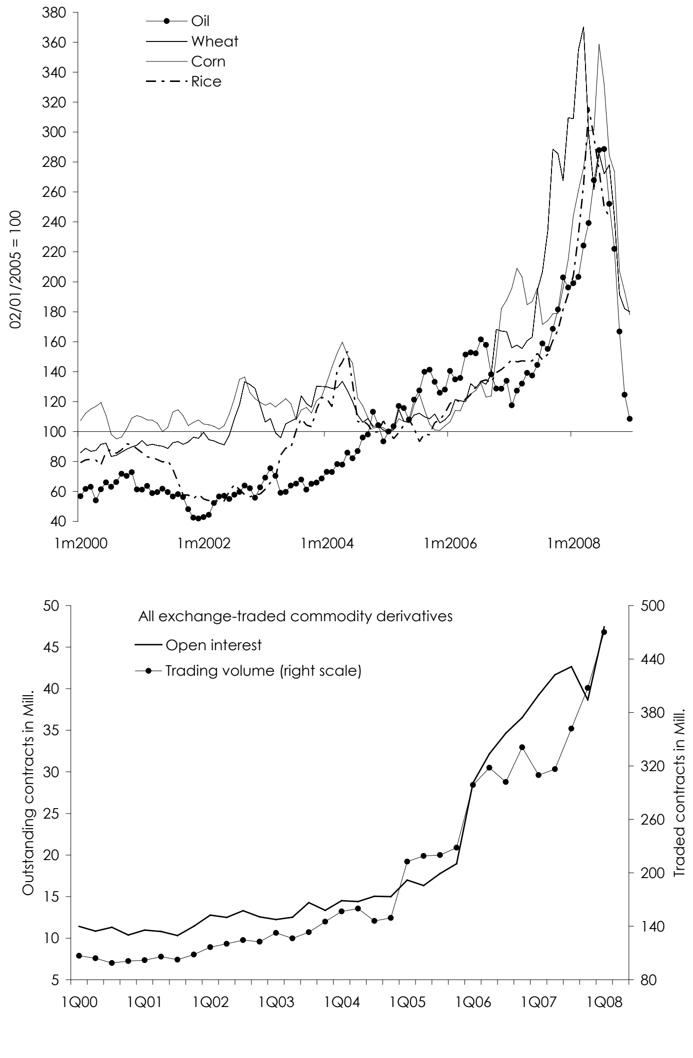
In the following chapters I shall first document the dynamics of trading activities in commodity derivatives markets in recent years, then I analyze the performance of technical trading systems in these markets as well as the price effects.

5. 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 has been tripling since then (figure 17). The boom in trading activities was particularly strong between the 2nd quarter of 2007 and the 1st quarter of 2008. Also the rise in number of outstanding derivatives contracts has been exceptionally great (figure 17). It does seem rather implausible that a fundamentals-oriented price discovery process should have called for such a strong increase in trading activities all of a sudden. Hence, this increase might rather be due to rising destabilizing speculation based on a general commodity "bull market" and carried out by the use of technical trading systems.

This presumption gets support from the fact that commodity future prices increased dramatically over this period, an increase which can hardly be explained by demand and supply conditions in commodity spot markets. Also the continuous deterioration of the general outlook for the global economy since mid 2007 would have let one to expect a dampening of the commodity price boom rather than its acceleration.

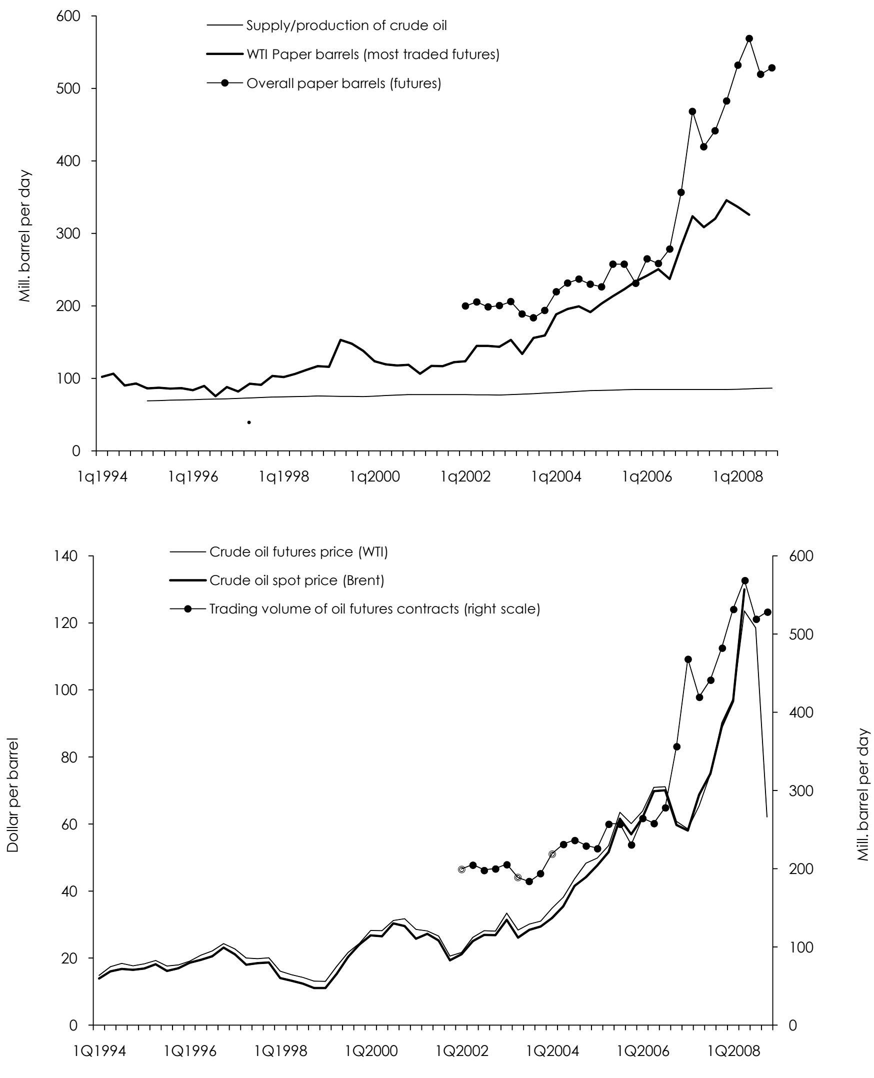
Figure 17: Dynamics of commodity futures prices and derivatives trading activities



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 18). By now, the daily trading volume of oil futures ("paper barrels") on the two most important exchanges (NYMEX and ICE) is almost seven times higher than the global production of physical oil (note, that the trading volume of "paper barrels" excludes exchange-traded oil options 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 (figure 18).

Figure 18: World market for crude oil, oil futures trading and oil price movements

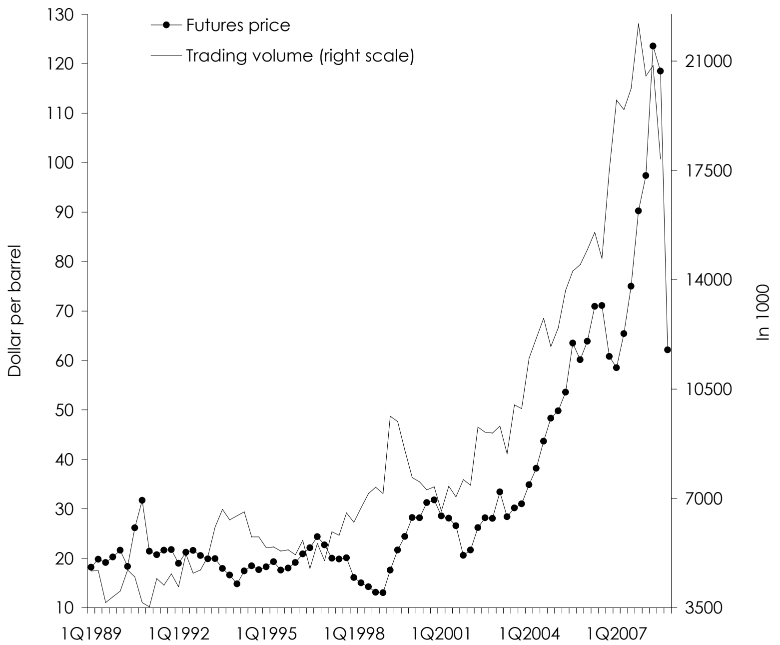


Source: Energy Information Agency (EIA), OECD, New York Mercantile Exchange (NYMEX), Intercontinental Exchange (ICE).

Also the futures markets for corn, wheat and rice experienced a tremendous rise in trading activities over the past 5 years (figure 19a and 19b to 19d in the annex). This development coincided with an unprecedented boom of the respective prices. 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 19a: Dynamics of oil futures prices and trading activity 1)



1) Most traded contract (NYMEX)

6. Performance of technical trading systems in commodity futures markets

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 behavior 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.

6.1 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 20a as well as figures 20b to 20d in the annex 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.

For the latter reason the study analyzes the interaction between the dynamics of commodity futures prices and technical trading on the basis of daily data. Even though most technical futures trading is nowadays done on an intraday basis and, hence, uses high frequency data (ranging from tick data to hourly data), it is the net long (short) overnight position of technical models in the aggregate which has the strongest impact on medium-term and long-term price trends. These "strategic positions" are usually derived from technical models based on daily data.

6.2 Model selection

The present 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 is analyzed (990 MA-models and 102 momentum models).[13])

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 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

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[13]) A similar set of technical models was used when testing the profitability and the price effects of technical currency trading (Schulmeister, 2006; 2008A; 2008B; 2008C). 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).

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, 2008B, 2008C). For these reasons the results of these studies as well as of the present study can hardly be attributed to "data snooping".

6.3 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. [14])

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).

[14]) 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.

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).[15])

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 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:[16])

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).[17])

[15]) 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, 2008C).

[16]) 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.

[17]) 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

6.4 How single models perform during the price boom 2007 to mid 2008

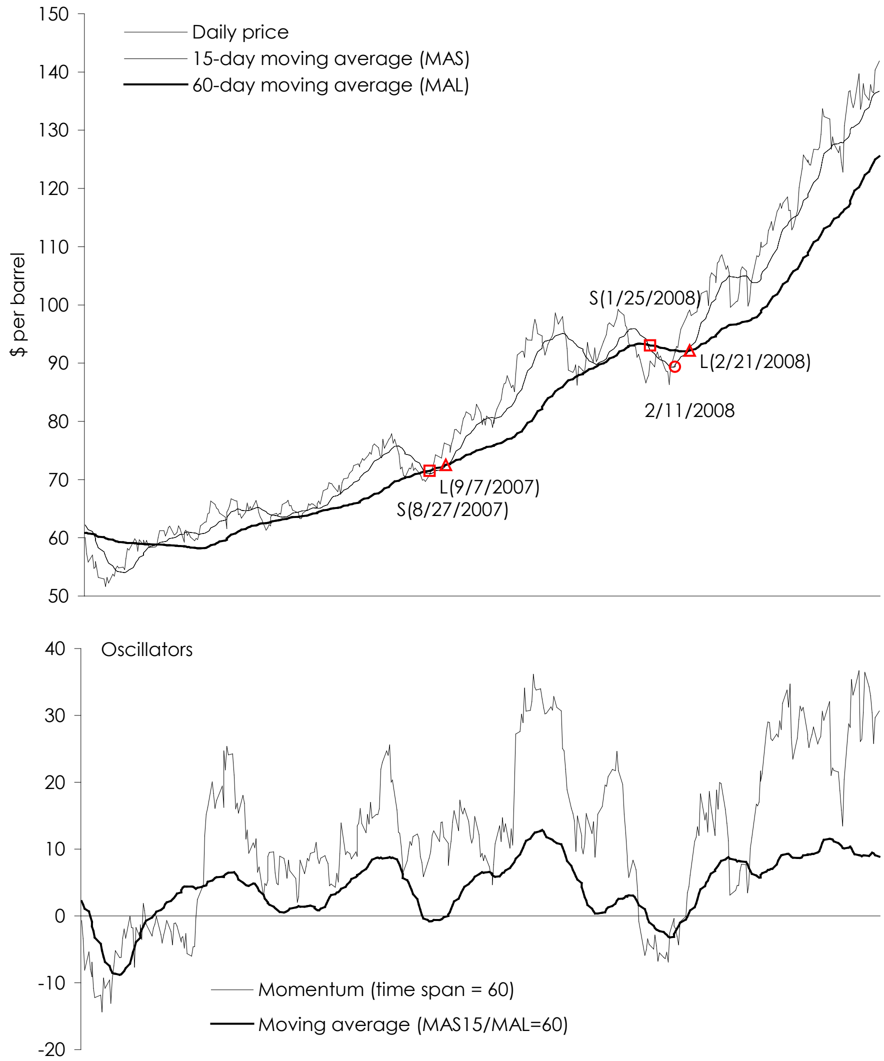
20a and table 2a demonstrate how a (slow) moving average model (MAS=15, MAL=60) and a (slow) momentum model (time span i = 60) perform in the WTI oil futures market between January 3, 2007 and June 30, 2008. First, I shall show how these models profit from persistent price trends. Over the months of June and July, the MAS is higher than the MAL (the MA oscillator is positive as is the momentum oscillator – figure 20a), 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 72.60 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 (-6.46%).

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 1, 2008 when it is closed at a profit of 23.18 cents (the sum of all single profits and losses realized at contract switches between September 7, 2007 and January 25, 2008 – table 2a). The last open position "rides" an even steeper upward trend of oil prices (figure 20a), it produces an overall profit of 39.16 cents between February 21, and June 30. Over the entire trading period, the MA model 15/60 would have achieved a (unleveraged) gross rate of return per year (GRR) of 26.7% per year, the momentum model 60 even 44.1% (note, that the number of profitable and unprofitable positions is equal just by chance in the case of the MA model). 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 20a also provides some first evidence about the time span over 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).

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 20a: Technical trading signals for WTI crude oil futures contract 2007 – 2008 (June)



As there was a general boom of commodity prices, the MA model 15/60 would have been profitable also in trading of corn futures (GRR: 38.9%), wheat futures (GRR: 29.3%), and rough rice futures (GRR: 9.4%). Figures 20b to 20d, and tables 2c to 2d, in the annex document the performance of this model as well as of the momentum 60 model in these three futures markets.

On August 27, MAS crosses MAL from above due to a steep fall in oil futures prices (the MA oscillator gets negative) and, hence, the MA model switches from long to short (figure 20a).

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: 06/30/2008

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
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
7/10/2007	l	0	72.60	0.00	-6.46
8/10/2007	n	31	70.60	-2.75	-10.14
8/10/2007	l	0	70.35	0.00	-10.14
8/27/2007	s	17	70.80	0.64	-8.42
9/7/2007	l	11	76.15	-7.56	-19.21
9/10/2007	n	3	75.85	-0.39	-19.55
9/10/2007	l	0	74.70	0.00	-19.55
10/10/2007	n	30	80.30	7.50	-7.69
10/10/2007	l	0	79.65	0.00	-7.69
11/12/2007	n	33	94.65	18.83	15.08
11/12/2007	l	0	93.60	0.00	15.08
12/10/2007	n	28	88.70	-5.24	8.24
12/10/2007	l	0	88.75	0.00	8.24
1/10/2008	n	31	94.20	6.14	13.58
1/10/2008	l	0	93.78	0.00	13.58
1/25/2008	s	15	90.35	-3.66	9.60
2/11/2008	n	17	91.85	-1.66	7.70
2/11/2008	s	0	91.85	0.00	7.70
2/21/2008	l	10	99.10	-7.89	0.56
3/10/2008	n	18	104.80	5.75	5.39
3/10/2008	l	0	103.80	0.00	5.39
..	..	..	..	..	..
..	..	..	..	..	..
..	..	..	..	..	..
6/30/2008	n	20	141.90	3.96	26.70

The profitability of the trading system

Gross rate of return per year	26.70
Net rate of return per year	26.35
Number of positions per year	
Long	2.68
Short	2.68
Neutral	0.00
Average duration of positions	
Long	99.25
Short	36.75
Neutral	0.00
Sum of profits per year	44.37
Profitable positions	
Number per year (NPP)	2.68
Average return	
Per position (RPP)	16.53
Per day (DRP)	0.166
Average duration (DPP)	99.50
Sum of losses per year	-17.67
Unprofitable positions	
Number per year (NPL)	2.68
Average return	
Per position (RPL)	-6.58
Per day (DRL)	-0.180
Average duration (DPL)	36.50

6.5 Performance of technical commodity trading 1989 - 2008

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, 2008 (the analogous tables 2b to 2d, and 3b to 3d for corn, wheat and rice futures trading are to be found in the annex). The fastest (momentum) model operating with a time span of 10 days displays an average duration of profitable positions (DPP) of 20.1 days, hence, it focuses on (very) short-term trends. The other selected models produce much longer DPPs, up to 131.0 days in the case of the MA model 15/60.

Table 3a: Pattern of trading the WTI crude oil futures contract 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	16.16	12.76	10.26	11.32	14.84	13.61
Sum of profits per year	50.51	42.54	38.96	36.21	35.18	31.94
Profitable positions						
Number per year	5.33	4.31	3.64	3.13	2.87	1.95
Average return						
Per position	9.47	9.88	10.70	11.58	12.25	16.39
Per day	0.191	0.166	0.154	0.143	0.130	0.125
Average duration in days	49.50	59.64	69.48	80.80	93.96	131.03
Sum of losses per year	-34.35	-29.78	-28.70	-24.90	-20.35	-18.33
Unprofitable positions						
Number per year	14.51	7.64	6.15	4.20	3.23	2.62
Average return						
Per position	-2.37	-3.90	-4.66	-5.92	-6.30	-7.01
Per day	-0.340	-0.275	-0.256	-0.222	-0.214	-0.167
Average duration in days	6.96	14.15	18.21	26.70	29.46	41.94
Distribution of the single rates of return						
Mean	0.814	1.068	1.048	1.544	2.432	2.983
t-statistic	1.983	1.669	1.357	1.478	2.071	1.793
Median	-1.309	-1.462	-1.548	-1.741	-0.888	-2.192
Standard deviation	8.070	9.746	10.648	12.444	12.751	15.603
Skewness	4.352	2.876	1.949	2.269	1.463	1.586
Excess kurtosis	33.750	15.998	7.755	8.840	3.505	2.657
Sample size	387	233	191	143	119	89

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.

All of the selected models are profitable, their annual gross rates of return vary between 4.55% (the "fast" model M 10) and 16.35% (the "slow" model M 60 with lagged signal execution).

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

Time span i	10	10	35	35	60	60
Lag of signal execution		1		1		1
Gross rate of return per year	4.55	4.70	12.15	9.29	14.75	16.35
Sum of profits per year	59.84	49.57	41.09	36.78	38.24	35.54
Profitable positions						
Number per year	11.69	7.23	5.90	3.54	3.95	2.41
Average return						
Per position	5.12	6.86	6.97	10.39	9.68	14.74
Per day	0.255	0.203	0.158	0.145	0.145	0.135
Average duration in days	20.07	33.79	44.23	71.57	66.57	109.47
Sum of losses per year	-55.29	-44.88	-28.93	-27.48	-23.49	-19.19
Unprofitable positions						
Number per year	22.31	11.38	11.08	6.15	7.90	4.51
Average return						
Per position	-2.48	-3.94	-2.61	-4.47	-2.97	-4.25
Per day	-0.424	-0.372	-0.278	-0.246	-0.230	-0.190
Average duration in days	5.85	10.60	9.40	18.17	12.94	22.42
Distribution of the single rates of return						
Mean	0.134	0.252	0.716	0.959	1.245	2.362
t-statistic	0.634	0.657	1.650	1.239	1.544	1.733
Median	-0.950	-1.241	-0.920	-1.297	-1.109	-1.218
Standard deviation	5.436	7.302	7.885	10.609	12.229	15.778
Skewness	2.712	1.649	3.691	2.296	4.220	3.200
Excess kurtosis	14.657	5.528	23.054	9.009	21.625	12.446
Sample size	663	363	331	189	231	135

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 2 and 3):

- The number of unprofitable trades is much higher than the number of profitable trades; in many cases the models produce even twice 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 5 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 6 of the 12 selected models trading oil futures (tables 3a and 4a) exceeds 1.645. Hence, only for half of the models was the probability of making an overall loss smaller than 1%. The t-statistics are even lower when the same models trade corn and wheat futures (table 3b, 3c, 4b, 4c). Only in the case of trading rice futures do the models produce somewhat higher t-statistics (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, 21.2% of all models achieve a t-statistic greater than 2 and the average (gross) rate of return per year over these modes amounts to 16.4%. The t-statistic of 74.7% of all models lies between 1.0 and 2.0 (average rate of return: 11.9%), 4.0% generate a t-statistic smaller than 1.0 (average rate of return: 6.6%). The average annual gross rate of return (GRR) over all 1092 models is 12.7%.

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 3.8% and 2.4%, respectively. Hence, only one model produces a t-statistic greater 2 in corn futures trading, and only 52 models in the case of wheat futures trading. The same technical models perform much better in rice futures trading, their annual GRR amounts to 12.6%, 17.4% 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 2008 (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	44	4.0	6.62	0.872	3.97	0.159	71.68	8.34	-0.278	17.36
1.0 - <=2.0	816	74.7	11.93	1.568	3.33	0.149	82.20	5.85	-0.238	22.26
> 2.0	232	21.2	16.44	2.161	3.11	0.144	94.50	4.62	-0.213	26.75
All models	1092	100.0	12.68	1.666	3.31	0.148	84.39	5.69	-0.234	23.02
Moving average models	990	90.7	12.57	1.661	3.12	0.147	86.68	5.39	-0.229	23.93
Momentum models	102	9.3	13.70	1.710	5.10	0.161	62.14	8.58	-0.279	14.21
Models with lag = 0	546	50.0	12.65	1.660	3.53	0.150	81.47	6.50	-0.248	20.97
Models with lag = 1	546	50.0	12.71	1.671	3.08	0.147	87.31	4.88	-0.220	25.07
					Corn futures contract					
t-statistic of the mean of the single returns										
< 1.0	840	76.9	2.79	0.488	3.15	0.108	83.80	7.10	-0.183	21.03
1.0 - <=2.0	251	23.0	7.11	1.197	2.45	0.098	110.04	4.66	-0.144	31.10
> 2.0	1	0.1	11.53	2.059	6.00	0.115	45.69	9.54	-0.219	9.53
All models	1092	100.0	3.79	0.652	2.99	0.106	89.79	6.54	-0.174	23.33
Moving average models	990	90.7	3.74	0.644	2.78	0.105	92.92	6.20	-0.171	24.31
Momentum models	102	9.3	4.32	0.735	5.09	0.115	59.50	9.86	-0.207	13.87
Models with lag = 0	546	50.0	3.82	0.660	3.23	0.107	86.83	7.43	-0.184	21.26
Models with lag = 1	546	50.0	3.76	0.644	2.75	0.105	92.76	5.66	-0.165	25.41
					Wheat futures contract					
t-statistic of the mean of the single returns										
< 1.0	-	-	-	-	-	-	-	-	-	-
1.0 - <=2.0	1040	95.2	2.14	0.369	2.86	0.110	88.06	6.69	-0.162	25.32
> 2.0	52	4.8	6.96	1.182	3.81	0.129	64.83	7.51	-0.176	18.66
All models	1092	100.0	2.37	0.408	2.91	0.111	86.96	6.73	-0.162	25.00
Moving average models	990	90.7	2.55	0.440	2.66	0.111	90.51	6.35	-0.157	26.15
Momentum models	102	9.3	0.56	0.091	5.26	0.116	52.48	10.43	-0.215	13.91
Models with lag = 0	546	50.0	2.18	0.375	3.12	0.113	85.10	7.68	-0.171	23.15
Models with lag = 1	546	50.0	2.55	0.440	2.69	0.110	88.81	5.79	-0.154	26.86
					Rice futures contract					
t-statistic of the mean of the single returns										
< 1.0	19	1.7	5.77	0.837	4.92	0.135	55.90	9.88	-0.227	13.51
1.0 - <=2.0	883	80.9	12.02	1.615	3.02	0.121	95.84	5.87	-0.177	23.16
> 2.0	190	17.4	16.02	2.142	3.09	0.125	91.01	4.51	-0.155	25.77
All models	1092	100.0	12.61	1.694	3.07	0.122	94.30	5.71	-0.174	23.45
Moving average models	990	90.7	12.71	1.701	2.86	0.122	97.67	5.40	-0.171	24.43
Momentum models	102	9.3	11.60	1.619	5.07	0.129	61.60	8.64	-0.207	13.94
Models with lag = 0	546	50.0	12.52	1.686	3.30	0.123	90.94	6.47	-0.183	21.40
Models with lag = 1	546	50.0	12.70	1.701	2.84	0.121	97.67	4.94	-0.165	25.50

Table 6: Components of the profitability of 1092 trading systems by types of models
Moving average and momentum models, daily data, 2007 to 2008 (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					
Net rate of return										
< 10	148	13.6	6.54	0.185	3.28	0.200	74.0	6.69	-0.290	23.2
10 - <= 20	379	34.7	15.92	0.463	3.42	0.203	73.3	6.76	-0.251	22.4
20 - <= 30	370	33.9	24.99	0.716	3.36	0.195	79.7	6.05	-0.209	24.2
> 30	195	17.9	36.31	0.981	3.64	0.196	82.0	5.77	-0.192	18.4
All models	1092	100.0	21.36	0.604	3.42	0.198	77.1	6.33	-0.232	22.4
Moving average models	990	90.7	20.60	0.584	3.29	0.197	78.0	6.15	-0.230	23.1
Momentum models	102	9.3	28.77	0.799	4.73	0.208	68.3	8.08	-0.251	15.3
Models with lag = 0	546	50.0	20.43	0.571	3.17	0.197	80.5	5.60	-0.225	24.0
Models with lag = 1	546	50.0	22.30	0.637	3.67	0.199	73.7	7.06	-0.238	20.8
					Corn futures contract					
Net rate of return										
< 10	619	56.7	-2.77	-0.088	3.78	0.195	66.9	9.35	-0.371	16.1
10 - <= 20	178	16.3	14.64	0.422	3.92	0.177	74.8	6.33	-0.333	18.7
20 - <= 30	146	13.4	24.73	0.683	3.77	0.164	83.4	4.08	-0.366	20.1
> 30	149	13.6	37.49	0.920	3.58	0.171	93.7	2.62	-0.324	23.9
All models	1092	100.0	9.24	0.236	3.77	0.184	74.1	7.23	-0.358	18.1
Moving average models	990	90.7	8.81	0.229	3.57	0.182	75.0	6.87	-0.352	18.6
Momentum models	102	9.3	13.39	0.303	5.71	0.211	64.5	10.73	-0.412	13.8
Models with lag = 0	546	50.0	10.88	0.279	3.69	0.184	74.4	6.06	-0.333	20.0
Models with lag = 1	546	50.0	7.60	0.193	3.86	0.185	73.7	8.41	-0.382	16.2
					Wheat futures contract					
Net rate of return										
< 10	46	4.2	2.73	0.073	3.38	0.165	73.6	7.15	-0.298	22.2
10 - <= 20	72	6.6	16.25	0.451	3.62	0.168	77.0	5.36	-0.266	23.0
20 - <= 30	295	27.0	26.19	0.725	3.06	0.168	99.3	4.22	-0.211	32.0
> 30	679	62.2	42.04	1.093	3.75	0.219	81.5	4.71	-0.210	24.3
All models	1092	100.0	34.41	0.908	3.54	0.200	85.7	4.72	-0.218	26.2
Moving average models	990	90.7	35.64	0.937	3.36	0.200	88.2	4.36	-0.204	27.4
Momentum models	102	9.3	22.46	0.633	5.29	0.198	61.7	8.22	-0.345	15.2
Models with lag = 0	546	50.0	34.20	0.905	3.33	0.196	87.0	3.99	-0.189	28.5
Models with lag = 1	546	50.0	34.61	0.911	3.75	0.203	84.4	5.46	-0.246	23.9
					Rice futures contract					
Net rate of return										
< 10	184	16.8	4.50	0.108	2.64	0.190	100.6	9.55	-0.259	16.6
10 - <= 20	320	29.3	16.17	0.394	2.16	0.184	137.0	7.58	-0.170	22.4
20 - <= 30	503	46.1	24.91	0.590	1.91	0.183	135.0	5.18	-0.114	29.7
> 30	85	7.8	33.22	0.719	2.80	0.189	101.6	5.15	-0.142	23.1
All models	1092	100.0	19.56	0.461	2.18	0.185	127.2	6.62	-0.157	24.9
Moving average models	990	90.7	19.77	0.459	1.94	0.185	133.7	6.18	-0.154	26.0
Momentum models	102	9.3	17.51	0.482	4.43	0.177	64.2	10.83	-0.183	14.2
Models with lag = 0	546	50.0	19.84	0.464	2.03	0.182	129.4	5.90	-0.153	26.0
Models with lag = 1	546	50.0	19.27	0.459	2.32	0.187	125.0	7.33	-0.161	23.7

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, 2008C). 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.

In periods of strong and persistent commodity price trends ("bull" 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 shall first document how the same 1092 models perform over the recent period of rising commodity prices (January 2007 to June 2008). I will then elaborate the impact of the aggregated trading signals of the 1092 technical models upon commodity price movements.

6.6 Performance of technical models during the recent commodity price boom

Between January 2007 and June 2008, the 1092 technical models produce much higher profits than over the entire sample period (compare table 6 to table 5). The models achieve a GRR of 21.4% per year on average when trading oil futures markets, 9.2% when trading corn futures, 34.4%when trading wheat futures, and 19.6% 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 (in part also due to the small sample size; in oil futures trading, e. g., the models produced only roughly 15 open positions over the 18-months-period).

6.7 Profitability of trading systems over subperiods ex post and ex ante

The study divides the overall sample period of 19,5 years into 5 subperiods each lasting 4 years (except for the last period covering only 3,5 years). In this section the performance of the 1092 models over each subperiod is documented, both ex post (in sample) as well as ex ante (out of sample).

The ex-post-performance of all models over the subperiods in the oil futures market can be summarized as follows (table 7a). First, these models would have made losses in only 615 out of 5460 cases (1092 models over 5 subperiods). Second, the average profitability of technical oil futures trading over the first 4 subperiods but has recovered somewhat since 2005 (and especially since the beginning of 2007 – see table 6).

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, 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, 2008B and 2008C).

Table 7a: Performance of technical trading systems by subperiods
Ex post and Ex ante
WTI crude oil 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	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

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 overfitting 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 subperiod. Then the performance of the selected models is simulated over the subsequent subperiod.

Table 7a shows that the ex-ante-performance of the 25 best models in the oil futures market is similar to the average ex-post-performance 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. Also in the case of trading corn, wheat and rice futures is the ex-ante-performance of the 25 models which performed best over the preceding period similar to the similar to average ex-post-performance of all models (see tables 7b to 7d 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.

In the oil futures markets the mean annual rate of return of the (ex-post) best models (24,4%) is three times higher than the mean over all models (7,9%). 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 significantly lower than on average over all models (tables 8b to 8d in the annex).

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

WTI crude oil futures contract, 1993 to 2008 (June)

Variable	Mean	S.D.	t-statistic
		All models	
		N = 4368	
Gross rate of return	7.85	7.54	
NPP/NPL	0.597	0.181	
DRP/DRL	0.625	0.142	
DPP/DPL	3.918	1.454	
		The 25 most profitable models: Ex post	
		N = 100	
Gross rate of return	24.37	7.63	21.413
NPP/NPL	0.744	0.234	6.239
DRP/DRL	0.722	0.203	4.752
DPP/DPL	4.804	1.987	4.432
		The 25 most profitable models: Ex ante	
Gross rate of return	10.52	14.58	1.826
NPP/NPL	0.663	0.235	2.790
DRP/DRL	0.553	0.112	-6.313
DPP/DPL	4.315	1.740	2.264

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.

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 corn, wheat and rice futures trading (table 8a and 8b to 8d in the annex). 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 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 this difference is highly significant (table 8a and 8b to 8d in the annex).

7. Price effects of technical commodity futures trading

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.

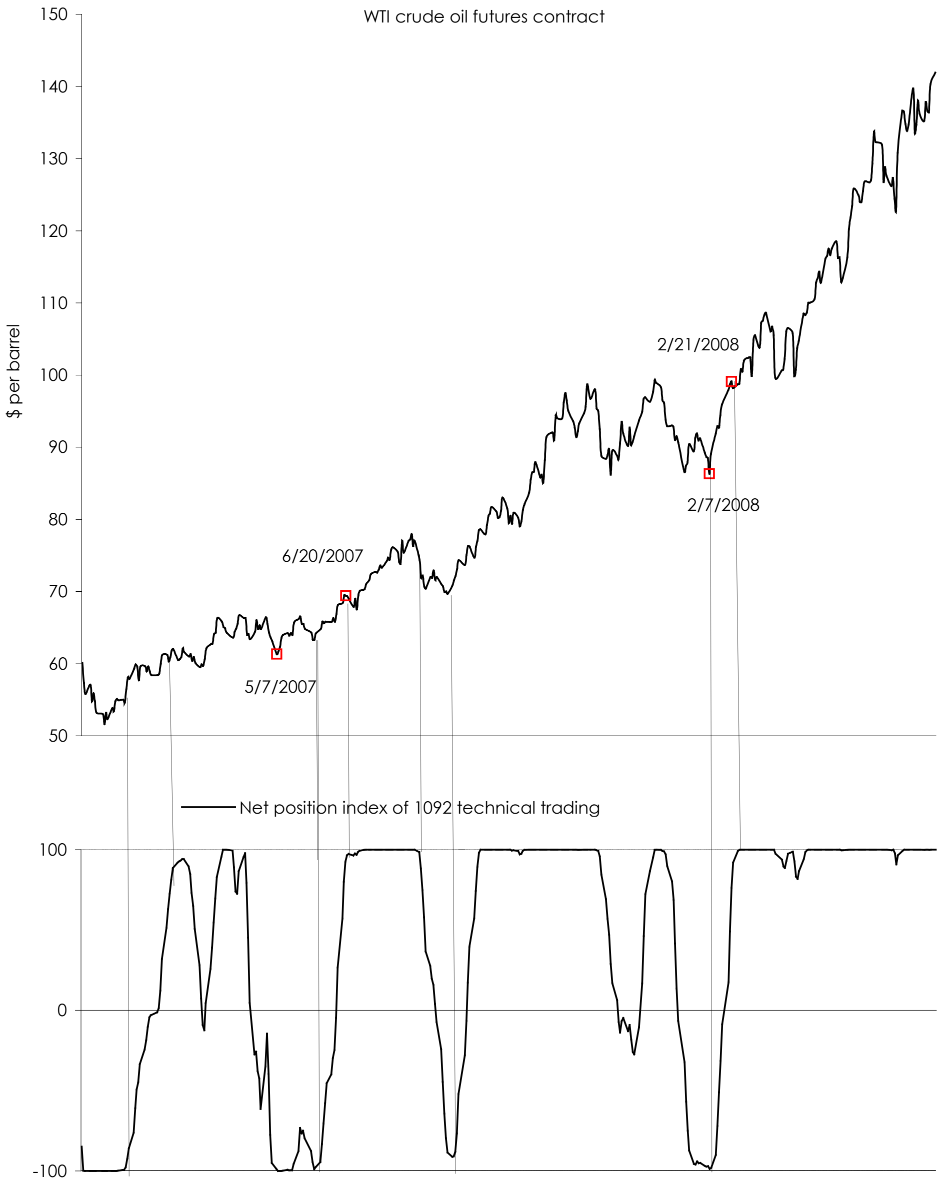
7.1 The aggregation of trading signals

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).[18])

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).

[18]) 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 21: Aggregate trading signals of 1092 technical models and the dynamics of oil futures prices, 2007 to 2008 (June)



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).

7.2 Similarities in position taking of technical models

Figure 21a shows the gradual adjustment of the 1092 technical models to oil futures price movements between January 2007 and June 2008 (the analogous figures 21b to 21d for corn, wheat and rice futures trading are to be found in the annex). On February 7, 2008, e. g., all models hold a short position due to a preceding 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.

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 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	39.27	98.89	99.45	-0.55
70 - 90	6.53	81.20	90.60	-9.40
50 - 70	4.12	60.52	80.26	-19.74
30 - 50	3.57	39.50	69.75	-30.25
30 - 10	3.30	20.00	60.00	-40.00
-10 - 10	3.00	-0.91	49.55	-50.45
-30 - -10	3.04	-19.74	40.13	-59.87
-50 - -30	2.98	-39.80	30.10	-69.90
-70 - -50	3.37	-60.94	19.53	-80.47
-90 - -70	5.73	-81.43	9.29	-90.71
< -90	25.09	-98.45	0.78	-99.22
Total	100.00	15.47	57.73	-42.27

	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	0.90	35.16	35.73	-0.57
30 - 10	10.32	17.77	18.92	-1.14
-10 - 10	77.15	0.01	1.50	-1.48
-30 - -10	10.61	-17.53	1.02	-18.55
-50 - -30	0.92	-35.84	0.39	-36.23
-70 - -50	0.06	-55.13	0.12	-55.25

An investigation into the trading behavior of the 1092 technical models over the entire sample reveals the following. First, most of the time the great majority of the models is 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. Figure 21a clearly demonstrates the gradual switching of technical models between long and short positions and the related price movements.

Table 10a: Similarity of different types of 1092 technical trading systems in holding open positions
WTI crude oil futures contract, 1989 to - 2008 (June

	Relative share of models holding the same - long or short - position		
	97.50%	95%	90%
	(|PI| > 95)	(|PI| > 90)	(|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	52.12	62.44	72.09
1.0 - <=2.0	59.40	65.10	71.69
> 2.0	58.85	65.48	74.99
By stability			
Stable models	61.40	66.05	71.97
Unstable models	56.12	64.26	72.66
By duration of profitable positions			
Short-term	50.02	58.61	69.38
Medium-term	67.46	72.13	77.50
Long-term	75.97	81.95	86.37
All models	58.67	64.36	71.50

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 39.3% (25.1%) of all days more than 95% of the models hold a long (short) position. Hence, on 64.4% 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 77.2% 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 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 behavior 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 71.5% of all days (4368 trading days between January 1989 and June 2008). The trading behavior 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 5 subperiods lasting 4 years).

The empirical evidence presented in figures 21a to 21d, 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.[19]

7.3 The interaction between technical trading and commodity price movements

At first, the possible interactions between the aggregate trading behavior 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 22) 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).

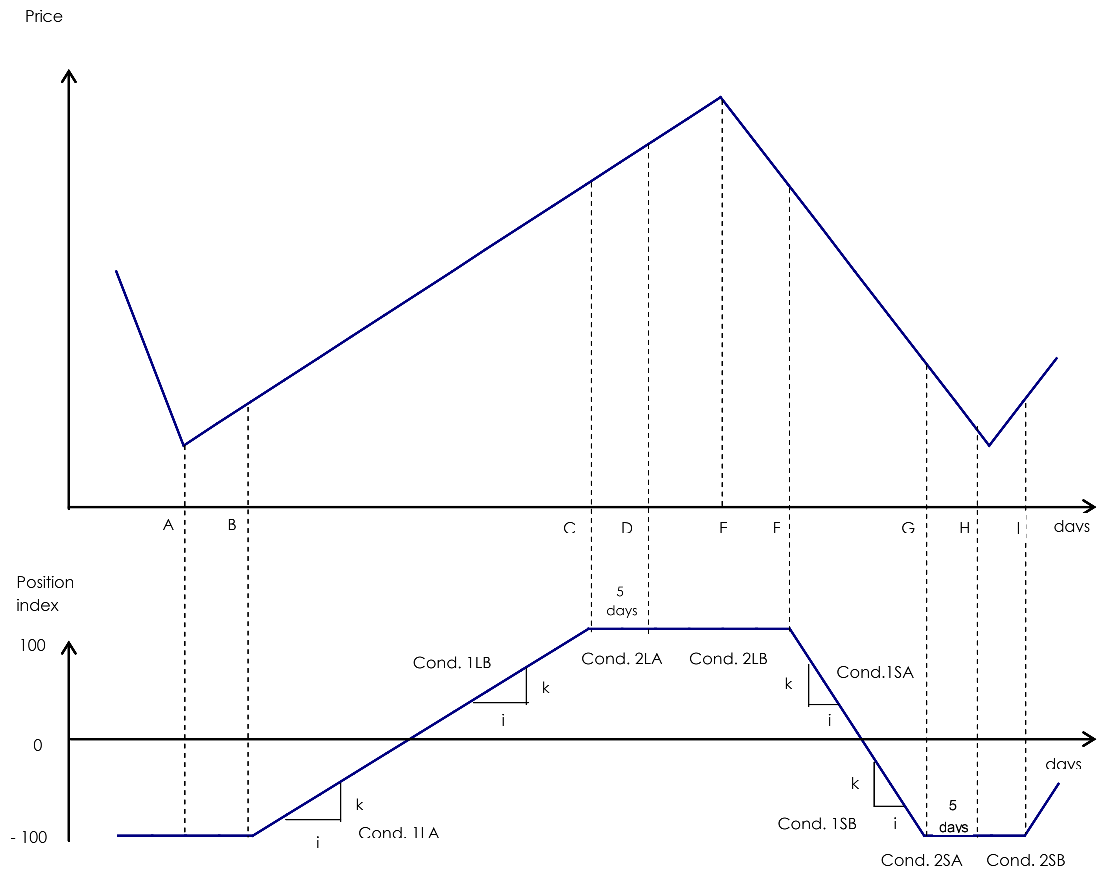
During the second phase of an upward trend (between B and C in figure 22) technical models produce a sequence of buy signals, the fastest models at first, the slowest models al last. The execution of the respective order flows then contributes to the prolongation of the trend.

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 22). Since technical models already hold a long position the prolongation of the trend is caused by an additional demand of non-

19) In order to figure out if and to what extent the aggregate gross and net positions of the 1092 models mimicries actual trading behaviour in the four US futures markets, I planned to compare the daily position indices to the actual daily net positions of different classes of traders in the four US markets. As the respective data are collected by the Commodity Futures Trading Commission (CFTC), I addressed myself to the CFTC, explaining the project and asking for the data. Unfortunately, the CFTC declined to provide the data for the following reason: "The Office of the Chief Economist can justify releases under certain circumstances, but these circumstances typically require that we document a very significant public interest...... Although we find that your proposal may provide useful information on trading strategies, it does not satisfy the public interest criterion, unfortunately." (email from chief economist Jeff Harris of October 10, 2008).

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).

Figure 22: Asset price trends and aggregate positions of technical models



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.[20])

[20]) 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, 2008C.

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 counterpositions (on day F in figure 22).

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 countermovements. 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 behavior 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 behavior 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: $[PI_t - PI_{t-i}] > k \cap [PI_{t-n} - PI_{t-n-1}] \geq 0 \cap [PI_t \leq 95]$
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: $[PI_t - PI_{t-i}] < -k \cap [PI_{t-n} - PI_{t-n-1}] \leq 0 \cap [PI_t \geq -95]$
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 545 (575) 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 413 (436) 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 247 (284) 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 1774 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 slightly more frequently realized (1420 cases).

Despite the different restrictions imposed on conditions 1L(S) and 2L(S) either of them is fulfilled on 3995 days out of the entire sample of 4905 days.[21]) These conditions are realized similarly often when simulating technical trading of corn, wheat and rice futures (tables 11b to 11d). This behavior 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 0.3168% between 1989 and June 2008, 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 2.685%. This highly significant difference (t-statistic: 18.5) can be explained as the

[21]) In order to avoid doublecounting 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

result of the simultaneous interaction between oil futures price movements and the changes of open positions by technical models.

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

Parameters of the conditions for CCP	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	545	2.6851	18.4700	575	-2.7726	-19.6171
	5	545	0.9092	2.8757	575	0.1597	-0.8092
	10	545	1.8023	3.9353	575	0.2555	-1.4561
	20	545	3.4970	5.5240	575	0.9437	-0.7357
	40	545	4.8141	3.7907	575	3.5256	1.7749
50	-5	413	4.0423	20.8164	436	-3.9062	-21.1652
	5	413	0.7876	1.9769	436	0.4399	0.5764
	10	413	2.0008	3.9006	436	0.3201	-1.0833
	20	413	3.7241	5.0333	436	1.2688	0.1073
	40	413	5.6179	4.2005	436	4.1288	2.4592
100	-10	247	6.7809	22.1019	284	-6.0070	-23.5869
	5	247	1.0311	2.5248	284	0.2055	-0.4419
	10	247	2.3853	3.8184	284	-0.3346	-3.0208
	20	247	3.5222	3.4514	284	0.8241	-0.7951
	40	247	5.8452	3.3536	284	4.7145	2.8390
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1774	0.4631	1.1487	1101	0.0163	-1.9861
	10	1774	0.5547	-0.3640	1101	0.2303	-1.8977
	20	1774	0.6004	-2.6014	1101	1.0152	-0.6893
	40	1774	0.9277	-4.5529	1101	2.9751	1.0630

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.

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 only in 7 out of 12 cases a negative sign and are in all cases (except for one) insignificantly different from the unconditional means.

Over the first 5 days subsequent to the realizations of condition 2L, i. e., when 97.5% of all models hold a long position, oil futures prices rise stronger than on average over the entire sample. However, this difference is statistically not significant (table 11a). Over the 10, 20, and 40 days following the realization of condition 2L oil futures prices tend to fall again, over the time spans of 20 and 40 days this tendency is even statistically significant. This result reflects the trend-reverting behavior of oil futures prices (and of asset prices in general). 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 the time spans of 5 and 10 days.

These results imply the following "stylized facts" about the interaction between oil futures price movements and the aggregate trading behavior of (trend-following) technical models. When the models are switching positions, prices continue to move in the direction congruent with the switch more often during phases of rising prices than during phases of falling prices. When almost all models are holding a long position, prices continue to rise only for a short period of time, whereas prices continue to fall for a comparatively longer period when the models are holding short positions.

In the case of rice futures trading, the interaction between the aggregate trading behavior 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 subphases 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 22).

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 behavior 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 22).

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 do not persist. Hence, the means of the conditional price changes following the realization of conditions 1LA differ only insignificantly from the unconditional means over time spans of 5 and 10 days.

The ex-ante oil futures price changes get significantly positive after the price trend has gained momentum (condition 1LB) and remain so following the realizations of condition 2LA (which are restricted to the first 5 days after 97.5% of all models have taken long positions). 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.

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	104	0.5119	0.3831	308	0.4673	0.6163
1B	5	309	0.8803	2.1419	127	0.3733	0.1387
2A	5	655	0.9581	3.3838	493	-0.4160	-3.8675
2B	5	1119	0.1733	-0.9410	608	0.0632	-1.2013
1A	10	104	1.8796	1.8601	308	0.1540	-1.4859
1B	10	309	2.0415	3.4768	127	0.7206	0.1972
2A	10	655	1.4466	3.2512	493	0.1399	-1.7520
2B	10	1119	0.0327	-2.8507	608	0.3037	-1.1452
1A	20	104	4.1264	3.0534	308	1.5958	0.7394
1B	20	309	3.5887	4.1283	127	0.4734	-1.0382
2A	20	655	1.9584	2.1050	493	0.5264	-1.6254
2B	20	1119	-0.1995	-4.9750	608	1.4116	0.4830
1A	40	104	6.4402	2.6834	308	4.7187	2.7743
1B	40	309	5.3411	3.3394	127	2.6942	0.1775
2A	40	655	3.0311	0.9972	493	3.0177	0.8936
2B	40	1119	-0.2949	-7.1600	608	2.9405	0.7155

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.

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 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.

8. Price stabilizing effects of a financial transaction tax and its revenue potential

In this chapter it is shown shall at first that the main results of the present study fit well into a picture of "stylized facts" of asset price dynamics in general. Then some channels are identified through which a general financial transaction tax might dampen short-term volatility and long-term swings of asset prices, and, hence, also of commodities prices. Finally, a new estimate of the revenues of such a tax is presented, based on global financial transactions in 2007.

8.1 Asset price overshooting and the stabilizing effects of a transaction tax

In a recent study on the feasibility of a general financial transaction tax the following "stylized facts" about asset price dynamics are elaborated. The results of the present, more detailed study on price fluctuations and trading practices in commodities markets fit well into the general picture of asset price overshooting as summarized in the following observations:

- Observation 1: There is a remarkable discrepancy between the levels of financial transactions and the levels of the "underlying" transactions in the "real world". E.g., the volume of foreign exchange transactions is almost 70 times higher than overall world trade. In Germany, the UK and the US, the volume of stock trading is almost 100 times bigger than business investment, and the trading volume of interest rate securities is even several 100 times greater than overall investment.

- Observation 2: For all types of assets, these discrepancies have risen tremendously since the late 1990s. In other words, financial transactions have expanded several times faster than transactions in the "underlying" markets for goods and services ("real-world-transactions").
- Observation 3: Trading in derivatives markets has expanded significantly stronger than trading in spot markets, this holds true for any kind of asset/instrument. In the world economy, derivatives trading volume is roughly 68 times higher than world GDP, whereas spot trading amounts to "only" 6 times world GDP (2007). In Europe and the USA, these ratios are significantly higher (the calculation of overall transaction volumes in financial markets is documented in *Schulmeister – Schratzenstaller – Picek*, 2008)
- Observation 4: Asset prices like exchange rates, stock prices or crude oil prices fluctuate in a sequence of long-term upward trends ("bull markets") and downward trends ("bear markets") around its fundamental equilibrium.
- Observation 5: These trends are the result of the accumulation of extremely short-term runs (on the basis of intraday data) which last longer in one direction than the counter-movements. When the market is "bullish", upward runs last longer than downward runs, when the market is "bearish", the opposite is the case.

These observations suggest that financial markets are characterized by excessive liquidity and by excessive long-run volatility of prices (i.e., strong and persistent deviations from their fundamental equilibria). Hence, these observations are rather in line with the "bull-bear-hypothesis" of asset price dynamics than with the "fundamentalist hypothesis". This can be concluded from the empirical evidence for the following reasons:

- Price expectations of market participants must be (very) heterogeneous and must have become progressively more so because otherwise trading (opportunities) had not risen so much faster than transactions in the "underlying" goods markets (observations 1 – 3).
- The spectacular rise of derivatives trading cannot be caused primarily by hedging activities simply because the volume of derivatives transactions is just much too big to be accounted for by hedging (observation 3).
- As a consequence, the greatest part of derivatives transactions has to be attributed to speculative trades between actors with heterogeneous price expectations. Whereas OTC trading is restricted to professionals, derivatives trading on exchanges is open to the general public. The fact that futures and options trading on exchanges has expanded faster than trading of OTC derivatives is indirect evidence that a rising number of amateurs participate in these activities.

- The pattern of asset price dynamics as a sequence of very short-term runs which accumulate to "bull markets" or "bear markets" and, hence, to long swings around the fundamental equilibrium suggests that the cumulative effects of increasingly short-term transactions are rather destabilizing than stabilizing. The growing importance of technical trading systems in financial markets contributes significantly to this pattern of price dynamics.

Even if the empirical evidence suggests that trading behavior and price dynamics in financial markets confirm rather the "bull-bear-hypothesis" as compared to the "fundamentalist hypothesis", there remains still the question whether or not a general and uniform financial transaction tax (FTT) will reduce specifically the "excessive" liquidity and the related overshooting of asset prices. For lack of experience with such a tax, an unambiguous answer to this question is certainly not possible. However, it seems at least probable that an FTT will dampen "excessive" liquidity to a larger extent than the "basic" liquidity needed for market efficiency. This can be presumed based on the following reasoning.

Surveys among foreign exchange traders reveal unambiguously that trading decisions are the more based on technical analysis (and the less on fundamentals) the shorter their time horizon is (see, e.g., *Menkhoff – Taylor*, 2007; *Gehrig – Menkhoff*, 2006). It seems highly probable for at least three reasons that this result also holds true for other asset markets (for which there are no surveys about trading behavior available). First, in normal times there are simply not enough relevant news on fundamentals to explain the frequent switches of professional traders between long and short positions during a trading day. Second, also the increasingly popular "day trading" of amateurs is almost exclusively based on technical models (see, e.g., *Deel*, 2000; *Velez – Capra*, 2000). Third, also the so-called "automated trading systems" based on technical analysis process high frequency price data.

Since a general FTT makes transactions the more costly the shorter the time horizon is, it will dampen specifically technical trading. At the same time, technical trading strengthens and lengthens price runs which in turn accumulate to medium-term trends. As a consequence, an FTT should reduce "excessive liquidity" stemming from transactions which are very short-term oriented and destabilizing at the same time.

Since an FTT increases transaction costs the more the lower they are (before tax), it will generally hamper derivatives trading to a greater extent than spot trading. Since spot transactions are more long-term oriented and, hence, based to a larger extent on fundamentals than (speculative) derivatives transactions one can presume that an FTT will hamper primarily short-term, non-fundamental transactions. At the same time, derivatives transactions for hedging purposes would not be affected by a low FTT (between 0.1% and 0.01%) since one usually needs just one transaction for hedging an open position stemming from "real-world-transactions" (e.g., future export earnings in foreign currency).

8.2 The revenue potential of a general financial transaction tax

The revenue potential of financial transaction taxes depends on the tax rate, on the turnover on the financial markets subject to taxation as well as on the impact of the tax on trading volumes. The concrete estimation procedure is described in detail in Schulmeister – Schratzenstaller – Picek (2008) where the revenue potential of a general FTT of 0.1%, 0.05%, and 0.01%, respectively, is estimated on the basis of transaction volumes in 2006. The same method is applied in the present study using 2007 transaction data instead of 2006 data. In addition, the potential revenues stemming from commodity derivatives trading are specified separately.

Table 13: Hypothetical transaction tax receipts in the global economy 2007
In % of GCP

		World			Europe			North America			Asia and Pacific		
	Tax rate in % / Reduction in transaction volume	0.1	0.05	0.01	0.1	0.05	0.01	0.1	0.05	0.01	0.1	0.05	0.01
Spot transactions on exchanges													
Total	Low	0.2039	0.1042	0.0214	0.2416	0.1237	0.0253	0.2958	0.1510	0.0311	0.3253	0.1661	0.0342
	Medium	0.1940	0.1019	0.0214	0.2313	0.1208	0.0253	0.2803	0.1479	0.0311	0.3084	0.1626	0.0342
	High	0.1833	0.0987	0.0204	0.2187	0.1170	0.0242	0.2647	0.1432	0.0296	0.2913	0.1575	0.0325
Derivatives transactions on exchanges													
Stock index	Low	0.2101	0.1313	0.0473	0.1754	0.1096	0.0395	0.2718	0.1699	0.0611	0.6154	0.3846	0.1385
	Medium	0.1576	0.1050	0.0420	0.1315	0.0877	0.0351	0.2038	0.1359	0.0544	0.4615	0.3077	0.1231
	High	0.1050	0.0788	0.0368	0.0877	0.0658	0.0307	0.1359	0.1019	0.0476	0.3077	0.2308	0.1077
Interest rates	Low	1.0945	0.7296	0.2919	1.2177	0.8118	0.3247	2.2898	1.5265	0.6106	0.4126	0.2751	0.1100
	Medium	0.7296	0.5472	0.2554	0.8118	0.6089	0.2841	1.5265	1.1449	0.5343	0.2751	0.2063	0.0963
	High	0.3648	0.2736	0.2189	0.4059	0.3044	0.2435	0.7633	0.5724	0.4580	0.1375	0.1031	0.0825
Currency	Low	0.0145	0.0103	0.0035	0.0002	0.0002	0.0001	0.0419	0.0299	0.0102	0.0015	0.0011	0.0004
	Medium	0.0103	0.0072	0.0031	0.0002	0.0001	0.0000	0.0299	0.0209	0.0090	0.0011	0.0008	0.0003
	High	0.0062	0.0052	0.0027	0.0001	0.0001	0.0000	0.0180	0.0150	0.0078	0.0007	0.0006	0.0003
Commodities	Low	0.0112	0.0070	0.0025	0.0198	0.0124	0.0045	0.0157	0.0098	0.0035	0.0028	0.0018	0.0006
	Medium	0.0084	0.0056	0.0022	0.0149	0.0099	0.0040	0.0117	0.0078	0.0031	0.0021	0.0014	0.0006
	High	0.0056	0.0042	0.0020	0.0099	0.0074	0.0035	0.0078	0.0059	0.0027	0.0014	0.0011	0.0005
Total	Low	1.3302	0.8783	0.3452	1.4132	0.9340	0.3687	2.6191	1.7361	0.6855	1.0323	0.6625	0.2495
	Medium	0.9059	0.6651	0.3027	0.9584	0.7066	0.3232	1.7720	1.3096	0.6007	0.7398	0.5162	0.2202
	High	0.4817	0.3618	0.2603	0.5036	0.3777	0.2778	0.9249	0.6952	0.5160	0.4473	0.3355	0.1910
OTC transactions													
Total	Low	0.8780	0.5853	0.2341	1.6666	1.1111	0.4444	0.6432	0.4288	0.1715	1.2587	0.8391	0.3356
	Medium	0.5853	0.4390	0.2049	1.1111	0.8333	0.3889	0.4288	0.3216	0.1501	0.8391	0.6293	0.2937
	High	0.2927	0.2195	0.1756	0.5555	0.4167	0.3333	0.2144	0.1608	0.1286	0.4196	0.3147	0.2517
All transactions													
	Low	2.4121	1.5678	0.6007	3.3214	2.1688	0.8384	3.5582	2.3159	0.8881	2.6163	1.6678	0.6194
	Medium	1.6853	1.2061	0.5290	2.3008	1.6607	0.7374	2.4811	1.7791	0.7820	1.8873	1.3082	0.5482
	High	0.9576	0.6800	0.4563	1.2778	0.9114	0.6352	1.4040	0.9992	0.6743	1.1581	0.8077	0.4753

Table 13 presents the estimated revenues of a general FTT for the world economy as a whole as well as for the main regions, differentiated by types of financial markets and by three scenarios about the reduction of transaction volume due to the introduction of an FTT. In the case of the medium "transactions-reduction-scenario" (TRS) overall tax revenues would have reached 1.685% of world GDP at a tax rate of 0.1%, and 0.529% at a tax rate of 0.01%. In North America and Europe tax revenues would be similar in size (relative to nominal GDP), in the Asian-pacific region FTT revenues would be lower by roughly one third than in North America and Europe.

Table 14: Hypothetical transaction tax receipts in the global economy 2007
In Bill. $

		World			Europe			North America			Asia and Pacific		
	Tax rate in % / Reduction in transaction volume	0.1	0.05	0.01	0.1	0.05	0.01	0.1	0.05	0.01	0.1	0.05	0.01
Spot transactions on exchanges													
Total	Low	110.7	56.6	11.6	42.5	21.8	4.4	45.2	23.1	4.8	20.8	10.6	2.2
	Medium	105.4	55.4	11.6	40.7	21.3	4.4	42.8	22.6	4.8	19.7	10.4	2.2
	High	99.6	53.6	11.1	38.5	20.6	4.3	40.4	21.9	4.5	18.6	10.1	2.1
Derivatives transactions on exchanges													
Stock index	Low	114.1	71.3	25.7	30.9	19.3	6.9	41.5	25.9	9.3	39.3	24.6	8.8
	Medium	85.6	57.0	22.8	23.2	15.4	6.2	31.1	20.7	8.3	29.5	19.7	7.9
	High	57.0	42.8	20.0	15.4	11.6	5.4	20.7	15.6	7.3	19.7	14.7	6.9
Interest rates	Low	594.4	396.3	158.5	214.4	143.0	57.2	349.6	233.1	93.2	26.4	17.6	7.0
	Medium	396.3	297.2	138.7	143.0	107.2	50.0	233.1	174.8	81.6	17.6	13.2	6.1
	High	198.1	148.6	118.9	71.5	53.6	42.9	116.5	87.4	69.9	8.8	6.6	5.3
Currency	Low	7.9	5.6	1.9	0.0	0.0	0.0	6.4	4.6	1.6	0.1	0.1	0.0
	Medium	5.6	3.9	1.7	0.0	0.0	0.0	4.6	3.2	1.4	0.1	0.0	0.0
	High	3.4	2.8	1.5	0.0	0.0	0.0	2.7	2.3	1.2	0.0	0.0	0.0
Commodities	Low	6.1	3.8	1.4	3.5	2.2	0.8	2.4	1.5	0.5	0.2	0.1	0.0
	Medium	4.6	3.0	1.2	2.6	1.7	0.7	1.8	1.2	0.5	0.1	0.1	0.0
	High	3.0	2.3	1.1	1.7	1.3	0.6	1.2	0.9	0.4	0.1	0.1	0.0
Total	Low	722.5	477.0	187.5	248.8	164.5	64.9	399.9	265.1	104.6	65.9	42.3	15.9
	Medium	492.0	361.2	164.4	168.8	124.4	56.9	270.5	199.9	91.7	47.3	33.0	14.1
	High	261.6	196.5	141.4	88.7	66.5	48.9	141.2	106.1	78.8	28.6	21.4	12.2
OTC transactions													
Total	Low	476.9	317.9	127.2	293.5	195.7	78.3	98.2	65.5	26.2	80.4	53.6	21.4
	Medium	317.9	238.4	111.3	195.7	146.7	68.5	65.5	49.1	22.9	53.6	40.2	18.8
	High	159.0	119.2	95.4	97.8	73.4	58.7	32.7	24.6	19.6	26.8	20.1	16.1
All transactions													
	Low	1310.1	851.5	326.3	584.9	381.9	147.6	543.2	353.6	135.6	167.1	106.5	39.6
	Medium	915.3	655.0	287.3	405.1	292.4	129.8	378.8	271.6	119.4	120.5	83.5	35.0
	High	520.1	369.3	247.8	225.0	160.5	111.9	214.4	152.6	102.9	74.0	51.6	30.4

Since financial transactions continued to grow faster than (nominal) GDP, the estimated share of FTT revenues in GDP is by roughly 10% higher for 2007 as compared to 2006. E. g., in Schulmeister – Schratzenstaller – Picek (2008) global FTT revenues were estimated for 2006 at 1.523% and 0.485% of world GDP, based on tax rates of 0.1% and 0.01%, respectively. These estimates rise to 1.685% and 0.529% of world GDP in 2007 (compare table 13 to table 10 in Schulmeister – Schratzenstaller – Picek, 2008).

Table 14 shows the estimated FTT revenues in absolute values. Under the condition of the medium TRS, overall revenues would have amounted to 287.3 bill. $ in 20007, even at the small tax rate of 0.01% in. More than half of the revenues (164.4 bill. $) would stem from derivatives transactions on exchanges (these transactions could be taxed most easily due to the use of electronic settlement systems). The greatest part of these revenues would originate from trading interest rate contracts (138.7 bill. $). Transactions of commodity derivatives on organized exchanges would contribute relatively little to the overall revenues of a general FTT since trading volume of commodity contracts is much smaller than trading volume of interest rate contracts and stock index contracts (note, however, that the estimates of tables 14 and 15 do not include commodity derivatives transactions in the OTC market due to lack of data).

8.3 Economic effects of a general financial transaction tax

There are two main motives for proposing a general and uniform FTT. The first rationale lies in dampening excessive liquidity in financial markets and in mitigating the related overshooting of asset prices, in particular of exchange rates, stock prices, interest rates, and commodities prices. The second reason for the introduction of a general FTT consists of its revenue potential. In addition to that, such a tax would roughly compensate for the – distorting – exemption of financial services from VAT in the EU. If this were not the case, a VAT on financial services would yield roughly 0.7% of GDP (see *Huizinga*, 2002). As table 13 shows, the estimated FTT revenues in Europe at the low rate of 0.01% come very close to the hypothetical revenues from a VAT on financial services.

Since the uniform tax rate of a general FTT refers to the notional value of the respective transaction, the FTT will hamper primarily very short-term trading of derivative instruments, in particular, intraday trading of derivatives with high leverage ratios (i.e., short-term speculation). By contrast, spot transactions of stocks and interest rate securities as well as derivatives transactions aimed at hedging open positions from goods markets activities (i.e., future export earnings in a foreign currency) will not be markedly affected by an FTT between 0.1% and 0.01%.

As regards the used trading technique, a general and uniform FTT will dampen specifically technical trading based on intraday data. As survey studies show, there is a clear tendency that the shorter is the time horizon of a speculative transaction the more it is based on technical analysis (see, e.g., *Menkhoff – Taylor*, forthcoming). This finding is confirmed by the literature about "day trading" for practitioners (*Deel*, 2000; *Velez – Capra*, 2000). At the same time, technical trading strengthens short-term price runs which accumulate to medium-term and long-term trends. These "bull markets" and "bear markets" are particularly pronounced in the stock market, the foreign exchange market and in the commodities markets.

One can therefore conclude that a general FTT with a low and uniform tax rate will most probably reduce excessive liquidity in financial markets and, hence, will mitigate the instability of asset prices. If an FTT contributes to reducing the extent of overshooting of exchange rates, stock prices, interest rates, and commodities prices, it will be beneficial not only for those countries which implement such a tax but for the global economy as a whole. This presumption might also concern the prehistory of financial crises. Certainly, a FTT will not prevent the outbreak of financial crises or other global shocks like oil price shocks. However, a FTT might mitigate the depth of these crises insofar as such a tax will restrict the extent of asset price overshooting which usually precedes the outbreak of financial crises.

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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: 06/30/2007

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
1/3/2007	l	0	382.00	0.00	0.00
2/12/2007	n	40	408.50	6.94	63.30
2/12/2007	l	0	419.50	0.00	63.30
3/23/2007	s	39	410.50	-2.15	22.14
4/10/2007	n	18	361.00	12.06	63.41
4/10/2007	s	0	371.75	0.00	63.41
6/11/2007	n	62	394.50	-6.12	24.63
6/11/2007	s	0	402.00	0.00	24.63
6/13/2007	l	2	404.00	-0.50	23.20
7/6/2007	s	23	347.00	-14.11	-7.69
9/20/2007	l	76	366.00	-5.48	-13.13
11/12/2007	n	53	379.50	3.69	-6.60
11/12/2007	l	0	395.50	0.00	-6.60
2/11/2008	n	91	498.00	25.92	18.30
2/11/2008	l	0	510.50	0.00	18.30
4/10/2008	n	59	610.00	19.49	31.33
4/10/2008	l	0	623.50	0.00	31.33
6/10/2008	n	61	667.00	6.98	32.54
6/10/2008	l	0	693.00	0.00	32.54
6/30/2008	n	20	771.00	11.26	38.90

The profitability of the trading system

Gross rate of return per year	38.90
Net rate of return per year	38.74
Number of positions per year	
Long	2.01
Short	1.34
Neutral	0.00
Average duration of positions	
Long	128.67
Short	79.00
Neutral	0.00
Sum of profits per year	52.04
Profitable positions	
Number per year (NPP)	2.01
Average return	
Per position (RPP)	25.85
Per day (DRP)	0.174
Average duration (DPP)	148.33
Sum of losses per year	-13.14
Unprofitable positions	
Number per year (NPL)	1.34
Average return	
Per position (RPL)	-9.79
Per day (DRL)	-0.198
Average duration (DPL)	49.50

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: 06/30/2008

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
1/3/2007	s	0	486	0.00	0.00
2/12/2007	n	40	462	4.94	45.06
2/12/2007	s	0	476	0.00	45.06
4/10/2007	n	57	455	4.41	35.18
4/10/2007	s	0	465	0.00	35.18
4/25/2007	l	15	504	-8.39	3.14
6/11/2007	n	47	545	8.13	20.89
6/11/2007	l	0	556	0.00	20.89
8/10/2007	n	60	668	20.14	48.74
8/10/2007	l	0	685	0.00	48.74
11/5/2007	s	87	775	13.14	50.55
11/12/2007	n	7	754	2.71	52.58
11/12/2007	s	0	774	0.00	52.58
12/11/2007	l	29	933	-20.54	26.20
2/11/2008	n	62	1153	23.58	43.48
2/11/2008	l	0	1155	0.00	43.48
4/7/2008	s	56	975	-15.58	25.82
4/10/2008	n	3	950	2.56	27.68
4/10/2008	s	0	961	0.00	27.68
6/10/2008	n	61	797	17.07	36.34
6/10/2008	s	0	813	0.00	36.34
6/25/2008	l	15	890	-9.47	28.92
6/30/2008	n	5	898	0.90	29.25

The profitability of the trading system

Gross rate of return per year	29.25
Net rate of return per year	29.07
Number of positions per year	
Long	2.01
Short	2.01
Neutral	0.00
Average duration of positions	
Long	105.67
Short	75.67
Neutral	0.00
Sum of profits per year	41.22
Profitable positions	
Number per year (NPP)	3.35
Average return	
Per position (RPP)	12.29
Per day (DRP)	0.121
Average duration (DPP)	101.60
Sum of losses per year	-11.97
Unprofitable positions	
Number per year (NPL)	0.67
Average return	
Per position (RPL)	-17.83
Per day (DRL)	-0.495
Average duration (DPL)	36.00

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: 06/30/2008

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
1/3/2007	l	0	10.44	0.00	0.00
2/6/2007	s	34	10.12	-3.07	-32.91
2/12/2007	n	6	10.22	-0.99	-36.99
2/12/2007	s	0	10.50	0.00	-36.99
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
9/11/2007	l	32	11.32	-5.30	-29.50
10/10/2007	n	29	11.74	3.71	-21.61
10/10/2007	l	0	12.07	0.00	-21.61
12/10/2007	n	61	13.40	11.02	-5.95
12/10/2007	l	0	13.78	0.00	-5.95
2/11/2008	n	63	15.61	13.28	6.98
2/11/2008	l	0	15.90	0.00	6.98
4/10/2008	n	59	20.95	31.76	31.13
4/10/2008	l	0	21.44	0.00	31.13
5/29/2008	s	49	18.15	-15.35	17.21
6/10/2008	n	12	20.00	-10.19	9.72
6/10/2008	s	0	18.50	0.00	9.72
6/30/2008	n	20	18.50	0.00	9.36

The profitability of the trading system

Gross rate of return per year	9.36
Net rate of return per year	9.13
Number of positions per year	
Long	2.68
Short	2.68
Neutral	0.00
Average duration of positions	
Long	79.25
Short	56.75
Neutral	0.00
Sum of profits per year	29.81
Profitable positions	
Number per year (NPP)	0.67
Average return	
Per position (RPP)	44.43
Per day (DRP)	0.170
Average duration (DPP)	261.00
Sum of losses per year	-20.45
Unprofitable positions	
Number per year (NPL)	4.70
Average return	
Per position (RPL)	-4.35
Per day (DRL)	-0.108
Average duration (DPL)	40.43

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	0.31	1.46	1.01	6.67	7.31	8.24
Sum of profits per year	32.66	28.86	27.10	25.13	23.25	22.18
Profitable positions						
Number per year	5.54	3.64	3.23	2.97	2.31	1.64
Average return						
Per position	5.90	7.93	8.39	8.45	10.08	13.52
Per day	0.137	0.124	0.116	0.095	0.095	0.094
Average duration in days	43.08	63.83	72.05	88.60	106.53	143.97
Sum of losses per year	-32.36	-27.39	-26.09	-18.46	-15.94	-13.94
Unprofitable positions						
Number per year	20.77	9.85	7.69	4.26	3.69	2.67
Average return						
Per position	-1.56	-2.78	-3.39	-4.34	-4.32	-5.23
Per day	-0.256	-0.207	-0.197	-0.182	-0.134	-0.108
Average duration in days	6.09	13.47	17.19	23.84	32.28	48.29
Distribution of the single rates of return						
Mean	0.012	0.108	0.092	0.923	1.219	1.914
t-statistic	0.054	0.259	0.183	1.218	1.288	1.296
Median	-0.942	-1.724	-1.723	-1.816	-1.276	-1.732
Standard deviation	4.833	6.785	7.337	8.962	10.192	13.451
Skewness	4.233	2.712	2.069	1.971	2.030	2.334
Excess kurtosis	24.497	10.077	5.976	5.876	5.367	6.905
Sample size	513	263	213	141	117	84

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	1.78	3.22	4.75	2.57	1.56	4.34
Sum of profits per year	33.97	28.66	27.85	21.87	22.56	20.91
Profitable positions						
Number per year	6.15	3.85	3.28	2.20	1.85	1.85
Average return						
Per position	5.52	7.45	8.49	9.92	12.22	11.33
Per day	0.133	0.122	0.119	0.101	0.111	0.088
Average duration in days	41.39	61.17	71.14	98.23	110.17	129.33
Sum of losses per year	-32.19	-25.44	-23.11	-19.30	-21.00	-16.56
Unprofitable positions						
Number per year	18.72	8.92	7.13	4.72	4.36	3.44
Average return						
Per position	-1.72	-2.85	-3.24	-4.09	-4.82	-4.82
Per day	-0.292	-0.196	-0.176	-0.130	-0.130	-0.131
Average duration in days	5.89	14.54	18.45	31.46	37.08	36.75
Distribution of the single rates of return						
Mean	0.071	0.252	0.456	0.371	0.252	0.822
t-statistic	0.321	0.573	0.808	0.469	0.268	0.769
Median	-1.135	-1.627	-2.005	-2.629	-2.903	-2.355
Standard deviation	4.901	6.926	8.022	9.159	10.286	10.797
Skewness	4.413	3.236	2.691	2.366	2.065	1.930
Excess kurtosis	30.644	16.111	8.608	6.714	4.638	4.099
Sample size	485	249	203	135	121	103

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	10.67	10.42	10.72	15.22	11.60	10.54
Sum of profits per year	38.84	35.46	31.84	31.31	28.36	25.84
Profitable positions						
Number per year	5.69	4.15	3.33	2.36	2.00	1.49
Average return						
Per position	6.82	8.54	9.55	13.27	14.18	17.37
Per day	0.146	0.136	0.123	0.128	0.115	0.110
Average duration in days	46.77	62.89	77.91	103.63	122.82	157.34
Sum of losses per year	-28.17	-25.03	-21.12	-16.08	-16.77	-15.30
Unprofitable positions						
Number per year	16.36	8.56	6.61	4.62	3.28	2.77
Average return						
Per position	-1.72	-2.92	-3.19	-3.48	-5.11	-5.53
Per day	-0.285	-0.241	-0.201	-0.133	-0.140	-0.117
Average duration in days	6.04	12.12	15.92	26.12	36.38	47.31
Distribution of the single rates of return						
Mean	0.484	0.820	1.077	2.183	2.195	2.476
t-statistic	1.439	1.383	1.423	2.048	1.502	1.425
Median	-1.035	-1.624	-1.534	-1.304	-1.693	-2.478
Standard deviation	6.967	9.313	10.515	12.387	14.764	15.729
Skewness	6.247	4.498	4.017	3.125	2.638	2.207
Excess kurtosis	52.977	27.309	20.951	12.396	8.588	5.813
Sample size	430	248	194	136	103	83

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

Length i of MAS						
Length i of MAL						
Time span i	10	10	35	35	60	60
Lag of signal execution		1		1		1
Gross rate of return per year	0.31	1.75	8.21	9.77	2.26	4.17
Sum of profits per year	38.34	32.20	30.04	26.59	25.57	22.27
Profitable positions						
Number per year	12.00	6.36	5.85	3.38	4.41	2.36
Average return						
Per position	3.20	5.06	5.14	7.86	5.80	9.44
Per day	0.167	0.154	0.119	0.103	0.100	0.089
Average duration in days	19.16	32.78	43.11	75.95	57.86	106.04
Sum of losses per year	-38.03	-30.45	-21.83	-16.82	-23.31	-18.1
Unprofitable positions						
Number per year	22.31	12.97	12.77	5.95	10.05	5.23
Average return						
Per position	-1.70	-2.35	-1.71	-2.83	-2.32	-3.46
Per day	-0.282	-0.195	-0.193	-0.156	-0.212	-0.158
Average duration in days	6.06	12.07	8.85	18.15	10.93	21.96
Distribution of the single rates of return						
Mean	0.009	0.090	0.441	1.047	0.156	0.550
t-statistic	0.059	0.333	1.561	1.716	0.337	0.636
Median	-0.654	-1.121	-0.683	-0.790	-0.890	-1.195
Standard deviation	3.911	5.254	5.375	8.211	7.774	10.480
Skewness	4.030	2.930	3.401	2.833	5.619	3.954
Excess kurtosis	29.607	14.556	15.494	10.842	41.317	20.881
Sample size	669	377	363	182	282	148

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

Time span i	10	10	35	35	60	60
Lag of signal execution		1		1		1
Gross rate of return per year	1.88	3.89	2.47	0.88	0.22	0.95
Sum of profits per year	44.97	37.25	28.88	23.85	25.08	20.48
Profitable positions						
Number per year	11.95	7.18	6.26	2.97	5.28	2.87
Average return						
Per position	3.76	5.19	4.62	8.02	4.75	7.13
Per day	0.190	0.162	0.117	0.110	0.095	0.080
Average duration in days	19.81	31.98	39.34	73.05	49.85	89.36
Sum of losses per year	-43.09	-33.36	-26.42	-22.96	-24.86	-19.53
Unprofitable positions						
Number per year	21.54	12.36	11.95	7.13	10.92	5.44
Average return						
Per position	-2.00	-2.70	-2.21	-3.22	-2.28	-3.59
Per day	-0.336	-0.246	-0.222	-0.155	-0.244	-0.180
Average duration in days	5.96	10.96	9.95	20.73	9.31	19.94
Distribution of the single rates of return						
Mean	0.056	0.199	0.135	0.088	0.014	0.114
t-statistic	0.342	0.721	0.418	0.158	0.040	0.163
Median	-0.862	-1.148	-0.771	-1.449	-0.844	-1.472
Standard deviation	4.181	5.387	6.101	7.748	6.150	8.909
Skewness	2.880	2.213	4.284	2.755	4.507	3.535
Excess kurtosis	16.342	8.500	24.228	9.666	28.559	16.741
Sample size	653	381	355	197	316	162

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

Time span i	10	10	35	35	60	60
Lag of signal execution		1		1		1
Gross rate of return per year	21.81	11.31	11.83	13.00	16.08	10.25
Sum of profits per year	51.02	41.38	35.01	31.99	30.77	25.54
Profitable positions						
Number per year	12.92	7.64	6.26	3.59	4.41	2.10
Average return						
Per position	3.95	5.42	5.60	8.91	6.98	12.15
Per day	0.198	0.178	0.126	0.117	0.112	0.095
Average duration in days	19.94	30.38	44.49	76.01	62.14	127.83
Sum of losses per year	-29.21	-30.08	-23.18	-18.99	-14.69	-15.29
Unprofitable positions						
Number per year	16.61	12.36	9.59	5.99	7.23	4.15
Average return						
Per position	-1.76	-2.43	-2.42	-3.40	-2.03	-3.68
Per day	-0.272	-0.226	-0.267	-0.206	-0.161	-0.159
Average duration in days	6.46	10.76	9.04	16.49	12.58	23.17
Distribution of the single rates of return						
Mean	0.738	0.565	0.747	1.416	1.382	1.639
t-statistic	3.210	1.713	1.593	1.787	2.124	1.426
Median	-0.364	-0.904	-0.662	-0.905	-0.610	-1.578
Standard deviation	5.515	6.511	8.226	10.572	9.779	12.647
Skewness	6.679	5.435	5.117	3.398	5.137	3.329
Excess kurtosis	80.825	53.944	35.896	15.877	32.960	13.182
Sample size	576	390	309	179	227	122

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

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

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

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 = 4368		
Gross rate of return	6.38	6.63	
NPP/NPL	0.562	0.202	
DRP/DRL	0.665	0.263	
DPP/DPL	4.372	1.667	
	The 25 most profitable models: Ex post		
	N = 100		
Gross rate of return	18.66	3.54	33.375
NPP/NPL	0.817	0.181	13.892
DRP/DRL	0.893	0.369	6.143
DPP/DPL	3.988	1.681	-2.259
	The 25 most profitable models: Ex ante		
Gross rate of return	8.36	9.33	2.110
NPP/NPL	0.609	0.166	2.785
DRP/DRL	0.716	0.378	1.342
DPP/DPL	4.351	2.416	-0.086

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.

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 = 4368	
Gross rate of return	1.74	7.54	
NPP/NPL	0.482	0.173	
DRP/DRL	0.751	0.260	
DPP/DPL	3.584	1.268	
		The 25 most profitable models: Ex post	
		N = 100	
Gross rate of return	13.99	6.55	18.425
NPP/NPL	0.677	0.156	12.328
DRP/DRL	0.833	0.244	3.318
DPP/DPL	3.296	0.824	-3.404
		The 25 most profitable models: Ex ante	
Gross rate of return	1.29	9.08	-0.492
NPP/NPL	0.562	0.186	4.259
DRP/DRL	0.628	0.182	-6.606
DPP/DPL	3.323	0.677	-3.709

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.

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 = 4368	
Gross rate of return	10.18	13.68	
NPP/NPL	0.589	0.246	
DRP/DRL	0.768	0.354	
DPP/DPL	4.232	1.676	
		The 25 most profitable models: Ex post	
		N = 100	
Gross rate of return	22.16	11.88	9.935
NPP/NPL	0.906	0.336	9.377
DRP/DRL	0.993	0.379	5.878
DPP/DPL	3.550	1.413	-4.751
		The 25 most profitable models: Ex ante	
Gross rate of return	8.98	14.77	-0.805
NPP/NPL	0.600	0.216	0.502
DRP/DRL	0.750	0.308	-0.576
DPP/DPL		1.390	-3.503

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.

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)

	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	26.92	98.56	99.28	-0.72
70 - 90	5.72	81.75	90.88	-9.12
50 - 70	4.16	60.44	80.22	-19.78
30 - 50	3.35	40.61	70.31	-29.69
30 - 10	2.84	19.23	59.62	-40.38
-10 - 10	2.84	-0.17	49.91	-50.09
-30 - -10	3.04	-20.27	39.86	-60.14
-50 - -30	3.16	-40.49	29.76	-70.24
-70 - -50	4.08	-60.46	19.77	-80.23
-90 - -70	6.25	-81.44	9.28	-90.72
< -90	37.63	-98.63	0.69	-99.31
Total	100.00	-10.95	44.53	-55.47

	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	0.08	60.16	60.39	-0.23
30 - 50	1.56	36.00	36.51	-0.50
30 - 10	9.66	17.59	18.79	-1.20
-10 - 10	76.63	0.00	1.55	-1.55
-30 - -10	11.00	-17.76	1.18	-18.94
-50 - -30	1.03	-35.79	0.47	-36.26
-70 - -50	0.04	-53.48	1.65	-55.13

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	25.03	98.36	99.18	-0.82
70 - 90	5.62	81.26	90.63	-9.37
50 - 70	3.33	61.01	80.50	-19.50
30 - 50	2.74	39.74	69.87	-30.13
30 - 10	2.78	19.90	59.95	-40.05
-10 - 10	2.92	0.12	50.06	-49.94
-30 - -10	3.20	-20.01	39.99	-60.01
-50 - -30	3.37	-40.18	29.91	-70.09
-70 - -50	3.96	-60.85	19.57	-80.43
-90 - -70	8.26	-81.47	9.26	-90.74
< -90	38.80	-98.39	0.81	-99.19
Total	100.00	-16.44	41.78	-58.22

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	0.12	57.20	57.30	-0.09
30 - 50	1.36	36.04	36.73	-0.69
30 - 10	10.20	17.94	19.06	-1.12
-10 - 10	76.15	-0.12	1.52	-1.64
-30 - -10	11.12	-17.67	1.07	-18.74
-50 - -30	1.03	-35.06	0.63	-35.69
-70 - -50	0.02	-63.37	0.00	-63.37

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)

		Aggregate positions		
Net position index	Share in total Sample period in %	Mean of the net position index	Mean of the gross position index	
> 90	25.17	98.53	99.27	-0.73
70 - 90	5.08	80.76	90.38	-9.62
50 - 70	3.66	60.62	80.31	-19.69
30 - 50	2.74	39.85	69.92	-30.08
30 - 10	2.54	19.46	59.73	-40.27
-10 - 10	2.66	-0.42	49.79	-50.21
-30 - -10	3.37	-20.15	39.93	-60.07
-50 - -30	3.72	-40.36	29.82	-70.18
-70 - -50	4.49	-60.45	19.77	-80.23
-90 - -70	6.85	-81.48	9.26	-90.74
< -90	39.72	-98.69	0.66	-99.34
Total	100.00	-16.97	41.51	-58.49

		Aggregate Transactions		
	Share in total Sample period in %	Mean of the net transaction index	Mean of the gross transaction index	
> 70	0.00	0.00	0.00	0.00
50 - 70	0.04	53.21	54.03	-0.82
30 - 50	1.08	35.90	36.90	-1.00
30 - 10	9.37	17.41	18.45	-1.03
-10 - 10	79.07	-0.02	1.53	-1.55
-30 - -10	9.31	-17.32	1.09	-18.41
-50 - -30	1.12	-35.68	0.78	-36.46
-70 - -50	0.02	-62.27	0.00	-62.27
< -70	0.00	0.00	0.00	0.00
Total	100.00	0.00	3.47	-3.47

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%	95%	90%
	(|PI| > 95)	(|PI| > 90)	(|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	58.61	65.31	72.39
1.0 - <=2.0	69.73	74.62	81.68
> 2.0	100.00	100.00	100.00
By stability			
Stable models	70.85	73.93	78.45
Unstable models	58.25	64.43	71.90
By duration of profitable positions			
Short-term	47.56	56.50	67.80
Medium-term	64.31	70.40	76.08
Long-term	76.51	81.98	85.45
All models	57.50	64.56	71.98

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%	95%	90%
	(|PI| > 95)	(|PI| > 90)	(|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	55.60	64.04	72.74
1.0 - <=2.0	73.63	78.99	84.10
> 2.0	-	-	-
By stability			
Stable models	66.06	74.28	76.49
Unstable models	55.27	63.77	72.35
By duration of profitable positions			
Short-term	44.48	52.05	62.90
Medium-term	63.96	72.33	78.66
Long-term	79.37	81.97	84.62
All models	55.66	63.83	72.37

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%	95%	90%
	(|PI| > 95)	(|PI| > 90)	(|PI| > 80)
	Share in total sample period in %		
Types of models			
By the t-statistic of the mean rate of return			
< 1.0	51.32	51.32	57.72
1.0 - <=2.0	59.55	65.34	72.02
> 2.0	69.04	76.51	82.30
By stability			
Stable models	68.20	76.96	86.41
Unstable models	58.39	63.80	70.17
By duration of profitable positions			
Short-term	46.26	54.65	63.71
Medium-term	66.11	71.76	77.43
Long-term	78.32	81.19	84.78
All models	58.55	64.89	72.25

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

Parameters of the conditions for CCP	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	503	0.3990	2.2371	565	-0.2153	-2.2929
	5	503	-0.1799	-2.0174	565	0.0284	-0.7700
	10	503	-0.1410	-1.8945	565	0.0779	-0.9020
	20	503	-0.0529	-1.9086	565	-0.1480	-2.3519
	40	503	0.7707	-0.9132	565	-0.8558	-5.0889
50	-5	358	1.0132	4.0179	420	-0.4563	-2.9669
	5	358	-0.2669	-2.2047	420	0.0908	-0.3229
	10	358	-0.4606	-2.7560	420	0.0249	-0.9097
	20	358	0.2097	-0.9453	420	-0.1692	-2.1015
	40	358	1.0012	-0.4011	420	-0.9803	-4.8538
100	-10	228	3.1689	9.0385	257	-2.3691	-8.0580
	5	228	-0.3446	-1.8790	257	0.0180	-0.6001
	10	228	0.2364	-0.1464	257	-2.3691	-8.0580
	20	228	-0.0762	-1.2513	257	-4.0343	-11.5330
	40	228	0.6465	-0.7563	257	0.3307	-2.1307
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1183	0.4808	2.8773	1648	0.0329	-1.2833
	10	1183	0.8910	3.6226	1648	0.1323	-1.2513
	20	1183	2.0414	5.9366	1648	0.3385	-1.3487
	40	1183	3.4278	6.1678	1648	1.0161	-0.9050

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)

Parameters of the conditions for CCP	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	539	0.3414	2.0078	604	-0.4794	-4.8346
	5	539	0.0549	-0.4195	604	0.0002	-0.9328
	10	539	0.1252	-0.5085	604	0.2512	-0.0271
	20	539	0.0003	-1.4313	604	0.5791	0.2693
	40	539	0.6372	-0.8807	604	0.4483	-1.2962
50	-5	440	1.1574	5.6816	469	-1.2168	-8.5260
	5	440	-0.0172	-0.7284	469	0.1412	0.0633
	10	440	-0.1225	-1.3119	469	0.3226	0.2940
	20	440	-0.1288	-1.6253	469	0.4375	-0.1924
	40	440	0.4029	-1.2818	469	0.2449	-1.5931
100	-10	304	3.7166	13.4296	326	-3.4218	-17.0011
	5	304	0.1336	0.0091	326	0.3129	1.0788
	10	304	-0.1890	-1.3833	326	0.4723	0.8306
	20	304	-0.1113	-1.2961	326	0.6213	0.3139
	40	304	0.6485	-0.6462	326	0.0044	-1.7878
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1073	0.1370	0.0404	1669	3.4941	0.9695
	10	1073	0.2353	-0.1139	1669	4.8696	0.7513
	20	1073	0.6767	0.6697	1669	6.7031	-0.4665
	40	1073	1.7896	1.8543	1669	8.5833	-1.0434

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)

Parameters of the conditions for CCP	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	501	0.1269	0.1839	496	0.0519	-0.4178
	5	501	0.3127	0.7508	496	-0.0541	-1.2837
	10	501	0.7775	1.5123	496	0.0151	-1.3982
	20	501	2.0873	3.3515	496	0.0684	-1.7330
	40	501	2.6523	1.7420	496	1.5947	0.1319
50	-5	359	0.3549	0.9254	383	0.1824	0.0921
	5	359	0.4839	1.3086	383	-0.1219	-1.5169
	10	359	1.2018	2.3853	383	-0.1826	-1.9993
	20	359	2.6886	3.9157	383	0.1846	-1.1589
	40	359	3.6035	2.5955	383	2.1854	0.8787
100	-10	212	0.2877	-0.0988	233	0.5765	0.8136
	5	212	0.9793	2.3510	233	-0.6010	-3.4476
	10	212	1.9112	3.2743	233	-0.7701	-3.5409
	20	212	3.5906	4.4137	233	0.5237	-0.2778
	40	212	4.1600	2.6583	233	3.3682	1.7747
		More than 97.5% of all models hold the same type of open positions					
		Long positions (condition 2L)			Short positions (condition 2S)		
	5	1118	0.4435	2.0881	1762	-0.0016	-1.6850
	10	1118	0.8630	2.8360	1762	-0.1138	-3.1184
	20	1118	1.4596	2.6283	1762	-0.0922	-3.7597
	40	1118	2.5756	2.4449	1762	0.2037	-4.1635

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	83	-0.7698	-2.4325	316	0.2105	0.2723
1B	5	275	-0.1152	-1.2401	102	-0.2803	-1.1249
2A	5	563	0.0570	-0.5885	688	0.2139	0.4458
2B	5	611	0.9761	5.7872	960	-0.0967	-2.2723
1A	10	83	-0.7560	-2.2549	316	-0.0823	-1.1430
1B	10	275	0.1753	-0.3645	102	0.3613	0.1083
2A	10	563	0.2242	-0.3295	688	0.2290	-0.3419
2B	10	611	1.7383	6.5498	960	0.0630	-1.4863
1A	20	83	-1.3284	-2.7038	316	-0.4738	-2.7623
1B	20	275	0.6739	0.2097	102	0.7873	0.2523
2A	20	563	1.2072	1.9624	688	0.0396	-2.0881
2B	20	611	2.9126	6.8615	960	0.5527	-0.1231
1A	40	83	-1.0956	-2.0005	316	-0.9472	-4.4320
1B	40	275	1.6410	0.5286	102	-1.0840	-2.2386
2A	40	563	3.2116	4.4372	688	0.3327	-2.2886
2B	40	611	3.6234	4.6680	960	1.5058	0.8309

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)

Wheat futures contract, 1993 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	122	-1.0503	-3.9780	368	0.2693	0.8436
1B	5	318	0.3791	0.9863	101	-0.3257	-1.2682
2A	5	525	-0.9200	-5.8401	815	0.1618	0.2210
2B	5	548	0.3564	1.1889	854	0.2929	1.2705
1A	10	122	-0.8820	-2.7138	368	0.4132	0.6201
1B	10	318	0.1688	-0.2444	101	-0.0029	-0.5778
2A	10	525	-0.0068	-1.1325	815	0.2977	0.2213
2B	10	548	0.4672	0.7743	854	0.4229	0.9128
1A	20	122	-0.6697	-2.0421	368	0.7108	0.5730
1B	20	318	0.0788	-0.8782	101	-0.5718	-1.6923
2A	20	525	0.4354	-0.2057	815	0.1820	-1.2102
2B	20	548	0.9079	1.0344	854	0.6270	0.5173
1A	40	122	-0.7611	-2.1392	368	0.4443	-1.0711
1B	40	318	0.8521	-0.3101	101	-0.4917	-1.4416
2A	40	525	1.9964	1.8344	815	0.6017	-1.2211
2B	40	548	1.5926	0.9521	854	0.9269	-0.3473

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	104	-0.0652	-0.6173	296	-0.1980	-1.7422
1B	5	255	0.7078	1.7461	86	0.1400	-0.0537
2A	5	512	0.2459	0.4466	709	-0.0540	-1.6701
2B	5	606	0.6105	2.4783	1053	0.0391	-1.0061
1A	10	104	0.6873	0.4944	296	-0.1927	-1.8384
1B	10	255	1.4117	2.5283	86	-0.1480	-0.7445
2A	10	512	0.7512	1.6627	709	-0.2287	-2.8896
2B	10	606	0.9574	2.4693	1053	-0.0365	-2.0580
1A	20	104	2.4871	1.7567	296	0.3354	-0.6899
1B	20	255	2.7676	3.4591	86	-0.3323	-1.1191
2A	20	512	1.6052	2.0814	709	-0.0899	-2.5291
2B	20	606	1.3366	1.7511	1053	-0.0937	-3.0951
1A	40	104	2.9513	0.7869	296	2.6671	1.2432
1B	40	255	3.8593	2.6691	86	0.5609	-0.7220
2A	40	512	2.0657	0.8920	709	0.6008	-1.9011
2B	40	606	3.3281	3.2798	1053	-0.0603	-4.3973

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.