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Modeling iron ore spot and futures market

Examination of momentum effects

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Contents

1. Abstract

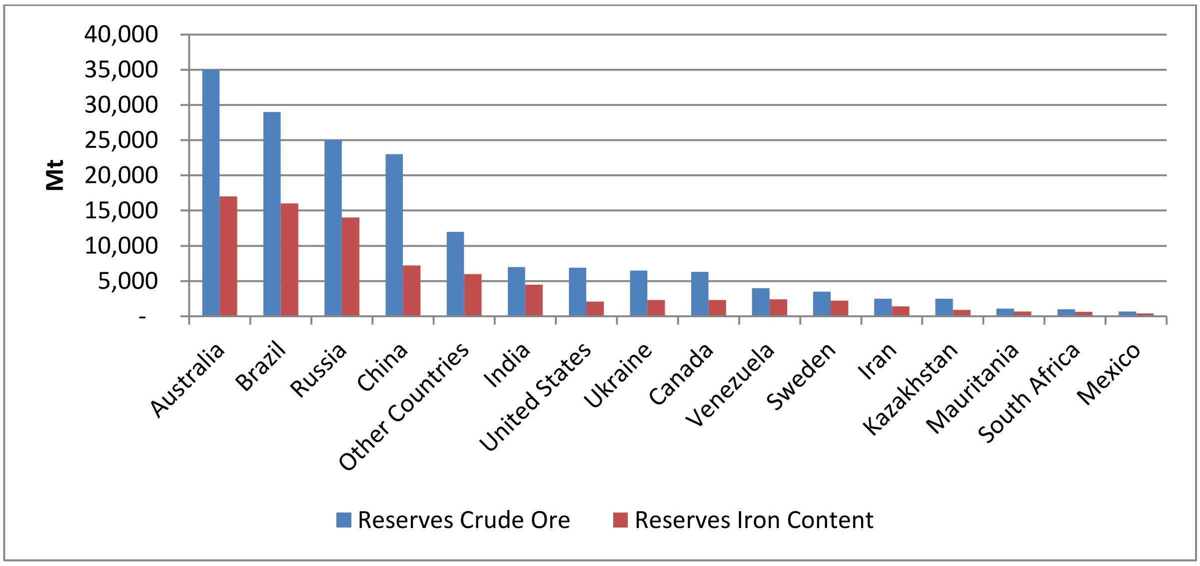
We document significant momentum returns in iron ore spot market. We find that the returns of the preceding three days have an explanatory power for the return of the following day, consistent with behavioural theories. However, we find that in iron ore futures market momentum returns are not persistent over time, and from preceding days' returns only the last day's return may have explanatory power to predict future returns. Nevertheless, back-tested trading algorithm has shown that, although in frictionless market there would be an opportunity to profitably trade on momentum, having realistic transaction costs eliminates these excess profits.

2. Introduction

Iron ore is a commodity product that is used to make steel, which is a main building material in construction and manufacturing industry.

The distribution of iron ore reserves is uneven across the world. Main deposits of iron ore are situated in Australia, Brazil, and Russia, comprising 52 percent of iron ore and 59 percent of iron content of the world reserves.

Figure 1 - World Iron Ore Reserves in Million tones (Mt) as of 2012



Source: USGS

The demand for iron ore comes from economies, where there is an upward trend of urbanization and industrialization. The reasons are simple. Steel can be produced either in blast furnaces from iron ore or infinitely recycling in electric arc furnaces. The products of steel are used in long-lived assets, such as buildings or machinery, and the incremental demand for steel appears in a situation, when there is a need to build up a stock of above mentioned long-lived assets. The demand for these assets happens mainly in emerging markets, where, unlike post-industrial, developed economies, the infrastructure development is still in its growth phase, and the urbanization level is low. A typical distribution of steel consumption by industry is given in the Figure 2.

Figure 2 - Chinese steel consumption by industry

	2001	2005	2008
Construction	57%	55%	54%
Machinery	15%	12%	18%
Automobile	6%	5%	6%
Home appliance	3%	2%	2%
Rail, shipping and fuel	5%	5%	5%
Other	15%	21%	15%

Source: (Rush, 2010)

Although the data depicts the steel consumption in Chinese industry, it is natural to see similar distribution on more aggregate level. Before the appearance of China on the global economic arena, Japan was the driving force for incremental demand of iron ore and its trade.

3. Emergence of Iron Ore Commodity Market

The international trade market of iron ore developed after the development Pilbara iron ore mines in Australia. Prior to that Australian government was reluctant to allow free export of iron ore due to its strategic importance. However, after it became apparent that iron ore deposits are abundant the restrictions had been lifted.

Japanese steel makers were interested in secure and stable supply of iron ore. They settled long-term contracts with fixed terms and encouraged production capacity increases of mines. High production capacities were keeping the price of iron ore stable and in depressed levels.

Few players, both in supply and demand side allowed such arrangements to be successful for decades. The main players from the demand side were Rohstoffhandel (a German procurement company, led by Thyssen), Erzkontor (another German group led by Salzgitter), Usinor, BSC and Nippon Steel (acting as the Champion of the Japanese steel mills). The main sellers were CVRD, BHP and Rio Tinto (Hamersley). The Indian iron ore price was negotiated separately and usually after the main price negotiations were over. Other smaller players usually agreed at the same price as the first price setter settled.[1]

This situation started to change after China joined the club of main importers of iron ore at the beginning of 21st century. As it is seen in Figure 1 - World Iron Ore Reserves in Million tones (Mt) as of 2012Figure 1 China has substantial iron ore reserves. Unfortunately the deposits are of low quality, with low iron ore content[2], which requires higher concentration of coaking coal in blast furnaces for steel production. Moreover, the main deposits of Chinese iron deposits are situated in Northern China, far from the shore and industrial centers and domestically extracted iron ore often loses its competitiveness due to transportation costs.

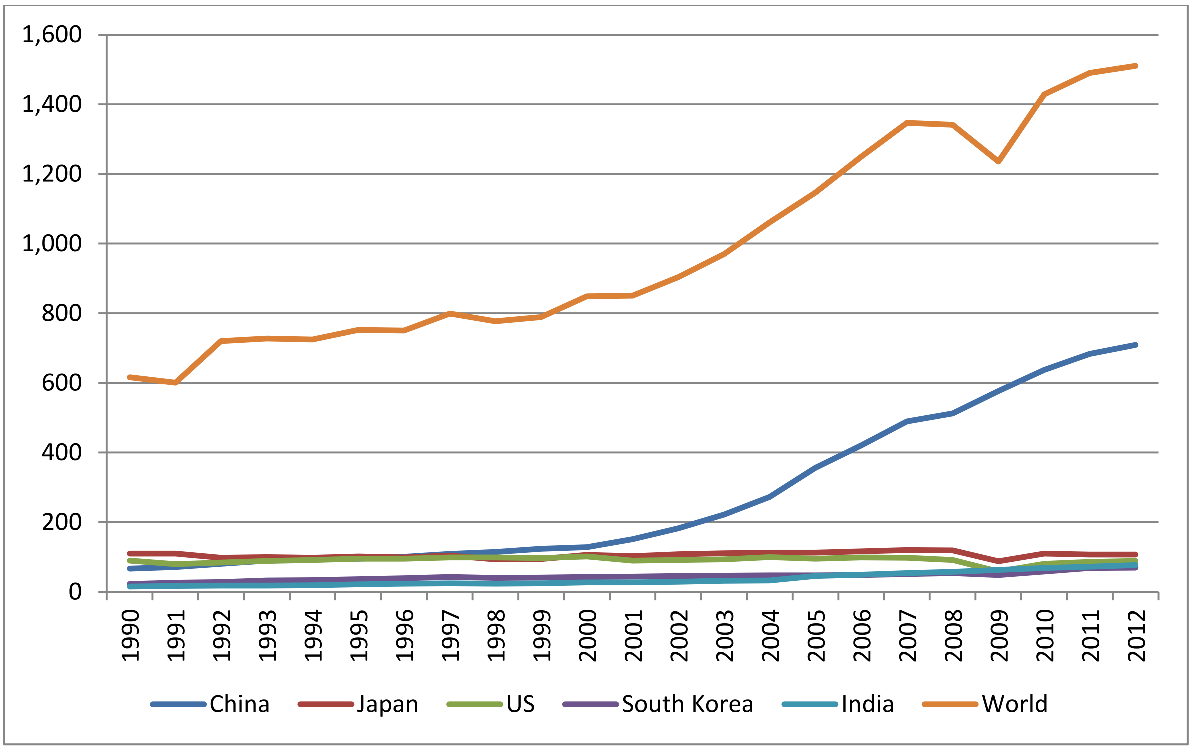
There were two reasons for changed price setting mechanism. First, buoyant demand of iron ore from China created a shortage of supply and broke the equilibrium of negotiating positions of buyers and sellers in the market (see Figure 3). Second, the microstructure of

[1] For details, see (Sukagawa, 2010)

[2] As you notice the neighboring Russia has almost the same amount of iron ore deposits, but almost twice the amount of iron content in its deposits.

Chinese steel industry was largely different from Japanese one. Only 50 percent of steel making capacity belongs to 18 steel making companies in China, while the remaining share belongs to medium to small scale companies (Sukagawa, 2010). As the share of small players increased, the fixed price setting regime became impractical as the incentives to breach the long-term contracts were too high.

Figure 3 - Annual steel production in Mt



Source: www.worldsteel.org

The increase of steel production in China is paramount. In 1990 it comprised only 11 percent of the world production, whereas in 2012 it was 47 percent. During the whole period, total annual production of steel worldwide increased by 894 Mt and 72 percent of the increase is contributed to China. Long-term stability of iron ore broke in 2007. In May 2010 classical negotiations failed and from 2011 further move to spot pricing intensified. Iron ore emerged as a commodity with price setting mechanism similar to other commodities; rather than fixed for a year, it is floating now on a daily basis.

4. Market Inefficiencies

4.1 Momentum Effect

In this paper iron ore spot and futures prices are analyzed to see whether there is momentum in its returns or not. Momentum in academic literature is defined as a phenomenon, when past positive (negative) returns are followed by future positive (negative) returns. Many studies have documented that in many markets trending effect, when future price behavior correlates with that of past is persistent (Titman, 1993) (Asness, 2009). Typically, for most of the markets, the correlation is positive for shorter periods, up to two years, but for longer periods, two to five years, there is a tendency that asset prices revert to the mean.

This abnormal behavior of price movements does not fit with the efficient market hypothesis. In academics, the efficiency of market is characterized by weak, semi-strong, or strong forms. Weak form efficiency implies that asset prices include information about all past returns. Semi-strong form efficiency assumes that asset prices include all publicly available information, and strong form efficiency implies that all information, both public and insider is already in prices. The violation of weak form efficiency will automatically annul stronger forms of efficiencies.

If the market is weak form efficient, it is not possible to make trades based on past price information and consistently beat the market. However, in one London Business School study back testing was performed for a trade, where performance-based top 20 percent of stocks are bought and 20 percent of worst performing stocks are sold short from 1955 to 2007 in UK stock market. The stocks that had outperformed the market most in the previous 12 months generated annualized return of 18.3 percent, whereas underperformers improved only by 6.8 percent, whereas the market rose by 13.5 percent per year during that period. In a subsequent study using data from 2000 to 2007 the same momentum effect was noticed in each of 16 international stock markets. (Dimson, 2008)

Moreover, other studies (Asness, 2009) (Maerkowitz, 2012) focused on momentum in all asset classes, while other studies (Rallis, 2007), (Qian Shen, 2007) concentrated on commodity futures. In all broad asset classes, stocks, bonds, currencies, and commodities there is a widespread phenomenon of trending behavior of prices, which violates the weak form market efficiency.

4.2 Factors behind momentum

The factors of abnormal returns are not well understood. In literature there are trials to identify global risk factors, macroeconomic and liquidity risks that are responsible for the premium (Asness, 2009). Authors found that liquidity risk is negatively related to momentum and its important increases over time, particularly following the collapse of Long-Term Capital Management and liquidity crisis of 1998. In other words, momentum strategies are doing better during illiquidity. This can be explained by the limited arbitrage principle, because the transaction costs during increased illiquidity premium become higher leading to the inability to profitably trade on momentum. However, in the same paper the authors could not find any significant macroeconomic factor that could explain the existence of momentum.

Another approach to understand the momentum is to look at the phenomenon from behavioral finance perspective. Momentum can be partly explained by the initial short-term under reaction and subsequent long-term overreaction of market participants to the additional information (Shefrin, 1985). Investors' willingness to sell winners reflects their anchoring bias on the purchase price or some arbitrary benchmark, additionally, they may believe that increased price brings higher risks and give them a strong incentive to sell the winners (Dimson, 2008).

Additional emotional factor that can contribute to the momentum is the regret aversion bias. Regret is the feeling that the opportunity has been missed. Regret is a reflection of hindsight bias, when the individual judges subjectively, that the past event was easily predictable. The feeling of regret can be particularly strong when the market is very volatile and individual investors more frequently face situations when they feel that they could have earned more by making correct market timing. Having this feeling of regret, investors may start chasing the past trends, which will explain short-term trending and overtrading (Shefrin, 1985).

To finalize, a disposition effect was noticed from trading records (Odean, 1998). Investors having U.S. discount brokerage accounts were selling winners more willingly than losers. This trading behavior if persistent will create market trending that we see across many asset classes.

Additional factors that can explain trending are related to the constraints of passive indexing of many institutional investors. Adherence to tight tracking-errors, mark-to-market valuation for regulators, and herding are additional explanations for momentum (Woolley, 2013). Asset price trends are in contradiction with value investing, which is well researched in academia and generally accepted standard of investing for institutional investors. However, the contradiction is illusionary due to different natures of investment styles. Value investing is a long-term approach based on a view that asset prices revert to their intrinsic values, whereas momentum is a strategy with active turnover generating short-term high returns with low-tracking errors. On one hand, an institutional investor, such as a pension fund is obliged by the regulation to keep its portfolio close to the benchmark in order to control risk. On the other hand, willingly or not, that institutional investor has to follow the crowd even if she believes that the assets in the benchmark are overvalued or undervalued. Imagine equity portfolio manager, who had a benchmark of international stock market of 1980s with increasingly high valuations of Japanese stocks. If the portfolio manager followed the fundamental value approach, she would have below average performance and possible flight of investors, while, following the passive market capitalization weighted index and slightly adding Japanese stocks' share, the portfolio manager would have lower tracking risk and higher returns. However, in situations of high volatility, market crashes, and abrupt changes of trends momentum strategy is likely to underperform due to more frequent wrong guesses, inability to exit from the position, and above average turnover of the portfolio.

Therefore, persistent momentum may not violate the market efficiency in a broader term, as the profit from the momentum strategy can be a compensation for the illiquidity risks, higher risks on longer horizons, or a compensation for a hedge.

4.3 Momentum Effect in Futures Markets

To mitigate the effect of illiquidity and high trading costs, many academics did their analysis on momentum in futures market. Not only futures market provide exposure to the asset classes with less trading and leverage costs, they also provide opportunities to go short in positions as easily as to go long making the trading strategies discussed actionable.

Futures market is a place of zero-sum game, and in this market, it is easier to identify abnormal returns, if any. In futures market the participants are of two categories, hedgers and speculators. They have different objective. Hedgers want to minimize the risk and are often subject to strict rules and constraints and, unlike speculators, for hedgers the control of risk is the main priority rather than risk-adjusted profit. For example, a central bank that follows fixed exchange rate or pegging exchange rate regime, may sell a foreign reserve currency to stop unwanted depreciation of local currency, even if the regulator understands that it will have losses on its balance sheet and will only decrease the speed of depreciation. In one research (Okunev, 2003) currencies from eight countries from 1975-2000 period were taken, and moving average strategy, which leverages momentum, generated 50-60 bps monthly return.

4.4 Momentum Effect in Commodity Markets: Unique Characteristics

In a paper - “Momentum in Asset Returns – Are Commodity Returns a Special Case?” (Schneeweis, 2008) the author stated that early academic studies exploring a possible violation of weak form efficiency in commodity markets found that the prices were not following a random walk (Cargill, 1975) and (Leuthold, 1972). However, the authors did not address the causes of such phenomenon.

There are several studies to identify momentum in commodity markets. Using data of 35 commodity futures over 1953-2003 period authors found momentum in short- and medium-term horizon. The monthly return was around 1.4 percent for the entire period. (Qian Shen, 2007). In another study (Pirrong, 2005) authors found 50-60 basis points momentum profits over short horizons for the data from January 1982 to November 2003.

In commodity markets storing and transportation costs are sources of friction that may cause persistent momentum profits (Williams, 1991). Authors examined the time series of spot prices of commodities and found significant autocorrelation and jumps in prices. They concluded that autocorrelation, high kurtosis and skewness are due to storage. In more recent analysis the authors linked the performance of momentum strategy to the storage of particular commodity (Gorton, 2007). Nevertheless, storage and transportation costs are only an additional factor to discuss in commodity futures case. The structure of any futures market is the same, there are speculators, who are liquidity providers to the hedgers and require compensation by above average return, which may be given away via momentum trade.

5. Momentum Effect in Iron Ore Spot and Futures Market

5.1 Sources and Data

In this paper we want to analyze newly formed iron ore spot and futures market to see whether there is a momentum in price behavior or not. Iron ore is a commodity and it is different from traditional financial assets. The commodity market has other characteristics that traditional stock or bond market lacks; storage costs, inventory levels, and hedging demand from producers are unique phenomenon of commodity markets.

For iron ore spot price, we will take one of the indexes published by The Steel Index (TSI), Spot TSI 62 percent FE CFR China Index. The name of the index tells prices of Chinese iron ore import under cost and freight (CFR) terms[3] with a 62 percent of iron ore content. Thereafter, when saying iron ore spot price, we will refer to this index. TSI indexes are based on actual transaction of 500 registered companies (The Steel Index). The Chinese iron ore import price became a global benchmark of iron ore spot price. The price is the underlying index for the mostly traded iron ore futures contract, and it is natural to choose that index as a representative of spot price.

The futures contract is traded in Singaporean Stock Exchange. The contract specifications are given in Figure 4.

[3] These terms oblige the supplier to include the cost of transportation up to the port of delivery into the price of a commodity.

Figure 4 - SGX OTC Iron Ore Futures

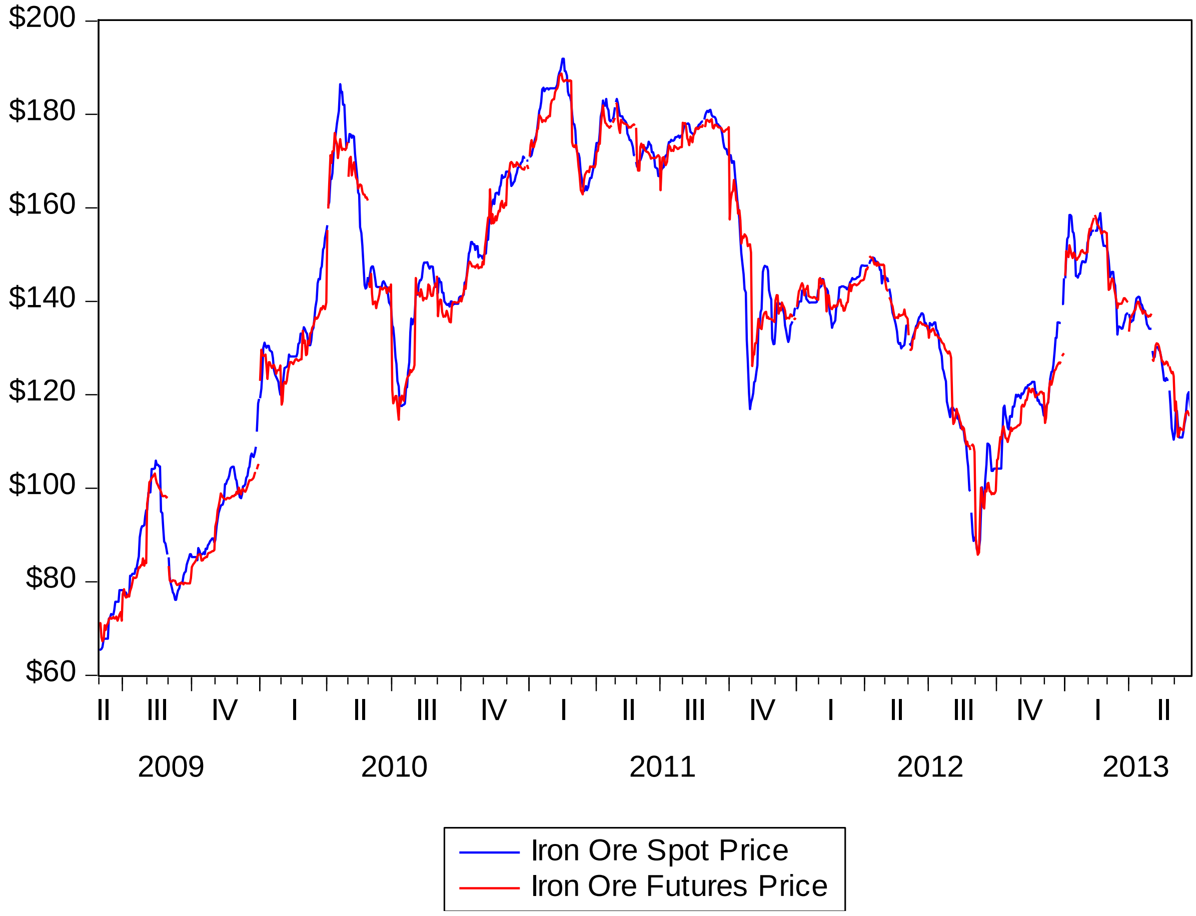
Contract Name	SGX TSI Iron Ore CFR China (62% Fe Fines) Index Futures
Contract Size	100 metric tonnes
Ticker Symbol	FEF
Minimum Price Fluctuation	US$0.01 per tick (US$1.00)
Contract Months	Up to 48 consecutive months
Trading Hours (Singapore Time)	T session: 8.00am – 8.00pm T+1 session: 9.00pm – 2.00am *Note:* ■ Contract is opened for trading on every business day except common holidays in Singapore and UK ■ There is no T+1 session for the expiring contract on its Last Trading Day
Trading Platform	SGX Quest
Daily Price Limit	No price limit
Negotiated Large Trade (NLT)	Minimum 5 lots
Position Limit	15,000 futures contracts (or 3,000 swap equivalent contracts) Equivalent to 1.5 million metric tonnes
Settlement Method	Cash settlement
Last Trading Day	Last publication day of The Steel Index (TSI) iron ore reference prices in the contract month
Final Settlement Price	Cash settlement using the arithmetic average of all The Steel Index (TSI) iron ore reference prices in the expiring month, rounded to 2 decimal places
Price Information	Bloomberg: SCIA index DES‹GO› Reuters: SZZF

Source: SGX website

As you see, futures contract is cash settled monthly derivative contract, when the underlying is the arithmetic average of TSI iron ore reference price, namely Chinese import price of the last month.

Both spot and futures data are daily, beginning from 1st of June 2009 and ending 24th of June 2013. The graph of price movements is depicted in Figure 5.

Figure 5 - Iron ore spot and futures daily price



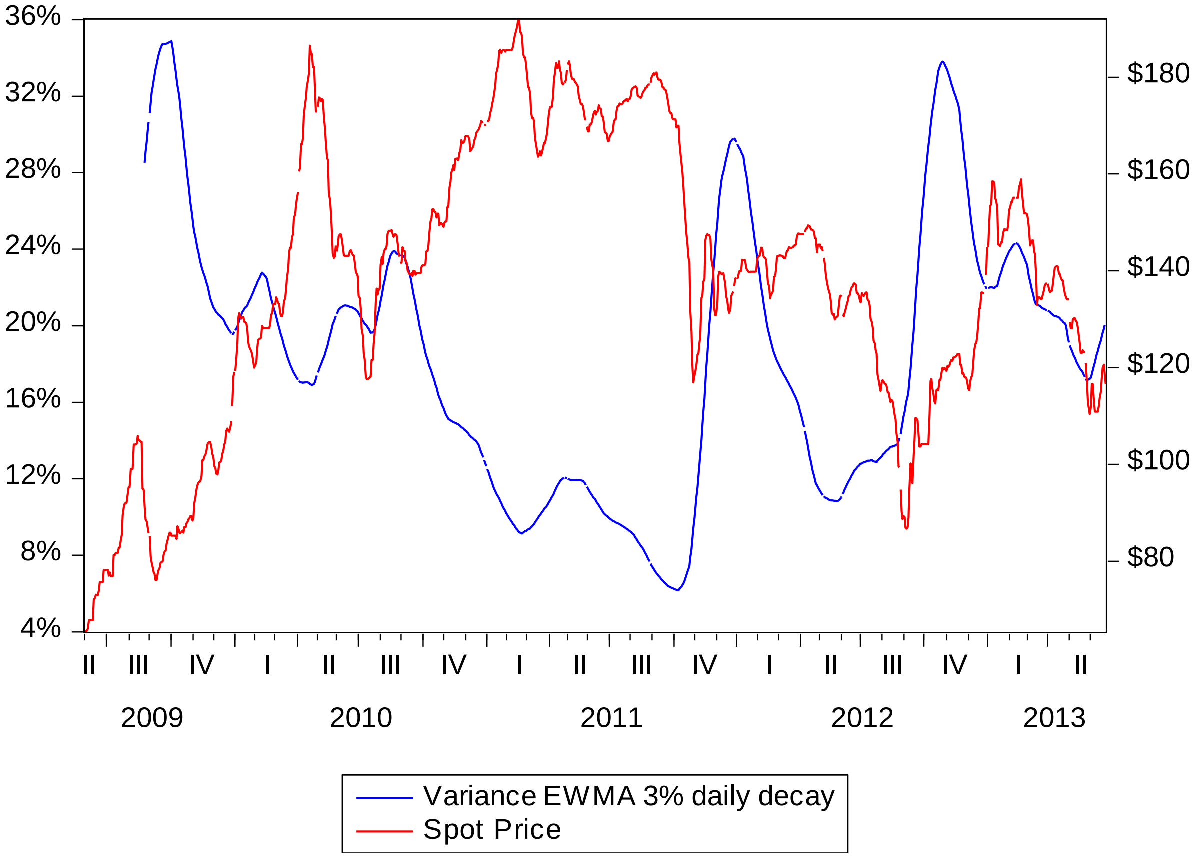
5.2 Data Characteristics

The price movement of iron ore is extremely volatile, almost tripling in one year and with big upside and downside surprises throughout the whole period.

Prices of iron ore can move due to both macroeconomic factors and short-term events. An example of long-term macroeconomic factors may be the robust demand of iron ore caused by high investment activity in China or decreased supply of iron ore due to shrinkage of deposits with high quality iron content. Short-term factors can be bottlenecks in ports, unexpected demand or excessive inventory due to short-term demand fluctuations.

The volatility is quite unstable with pikes and smooth periods. Closer look at spot returns and their volatility reveals the nature of price pattern (see Figure 6).

Figure 6 - Iron ore spot price and volatility



The summary statistics of spot and futures return indicates that return distribution is not normal, with high kurtosis and positive skewness[4], which are common for commodities (see Table 1, Table 2, and Table 3.

[4] Although the skewness of futures returns is negative it is explained by large rollover effects at the beginning of each month. The futures return distribution without considering the rollover effects is similar to spot return distribution (see Table 3).

Table 1

Summary Statistics - Spot Return	
Mean	0.07%
Standard Error	0.04%
Median	-
Mode	-
Standard Deviation	1.38%
Sample Variance	0.02%
Kurtosis	7.12
Skewness	0.11
Range	16%
Minimum	-9.26%
Maximum	6.74%
Sum	0.69
Count	1,024.00
Confidence Level(95.0%)	0.08%

Table 2

Summary Statistics -Futures Return	
Mean	0.07%
Standard Error	0.06%
Median	0.03%
Mode	-
Standard Deviation	1.97%
Sample Variance	0.04%
Kurtosis	34.42
Skewness	(0.61)
Range	35%
Minimum	-17.32%
Maximum	17.25%
Sum	0.68
Count	1,024.00
Confidence Level(95.0%)	0.12%

Table 3

Summary Statistics -Futures Return w/o considering rollover effect	
Mean	0.10%
Standard Error	0.03%
Median	0.00%
Mode	0.00%
Standard Deviation	0.98%
Sample Variance	0.01%
Kurtosis	12.69
Skewness	1.20
Range	13.88%
Minimum	-4.51%
Maximum	9.37%
Sum	1.05
Count	995.00
Confidence Level(95.0%)	0.06%

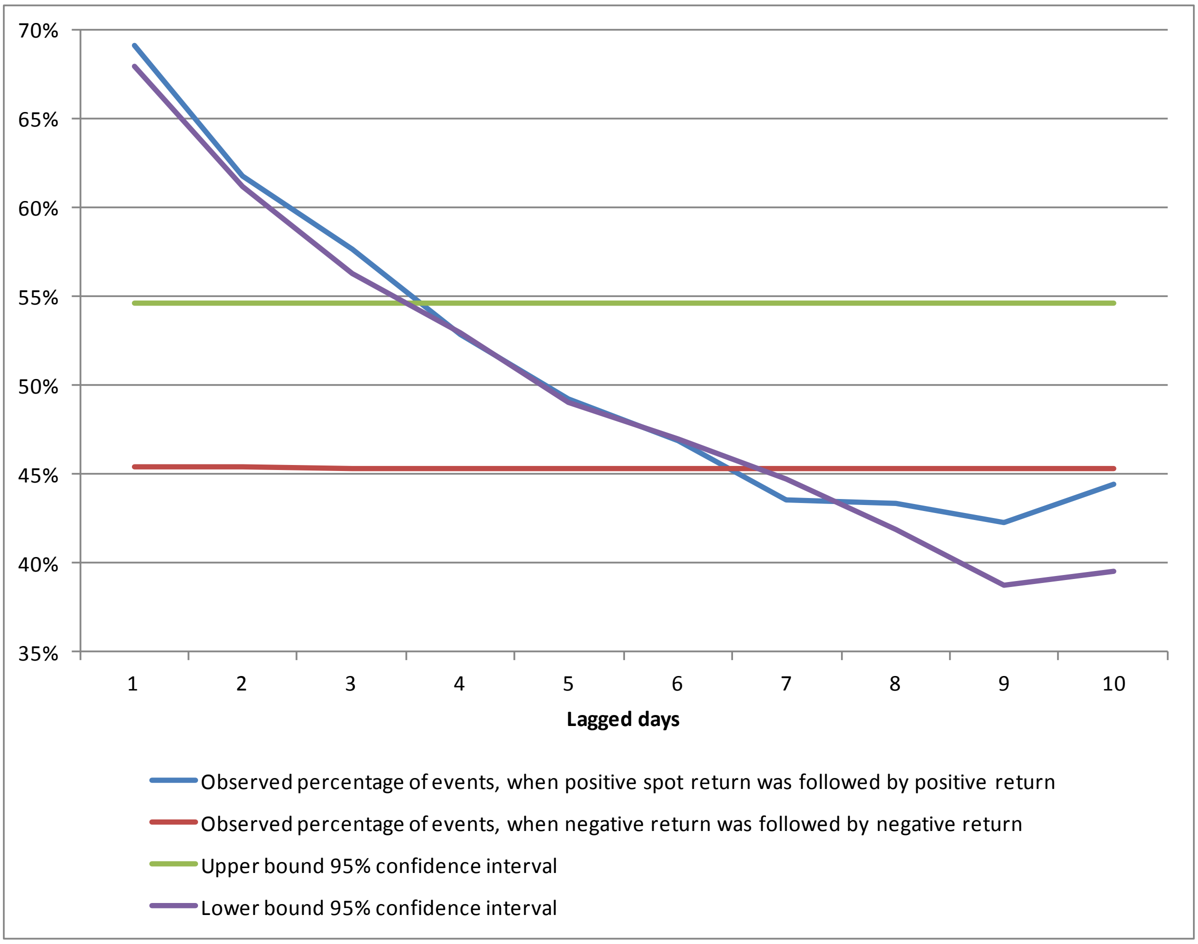
6. Predictability of Iron Ore Spot and Futures Returns' Direction

Having a look at the price patterns, interesting question arises. Whether past returns explain future returns in spot and futures market.

Let us implement a very simple test to gauge some peculiarities in the data. Assume the market is weak-form efficient and frictionless. In that case if we encounter a positive (negative) return a day prior to observation, the probability that the return on the following day will be positive (negative) is 50 percent. This statement must be correct in such a market, otherwise the investor will have information about probable direction of price move, based on historical data. The same holds if we took more distant observations rather than last day figure.

This hypothesis was tested both on spot and futures return data. The results for spot returns are given in Figure 7 and the results for futures return are in Figure 8 and Figure 9.

Figure 7 - Autocorrelation of spot daily returns



For spot returns the results are quite telling. If the spot return was negative (positive) yesterday there was an almost 70 percent chance that the direction of return would be on the same direction the following day. This strong link weakens as we take more distant days and becomes lower than 45 percent for the 10th day. Note that given the number of observations and based on Bernoulli distribution, it is easy to construct a confidence interval[5]. Combining the confidence interval with 95 percent confidence level and the observed values, we clearly see that the sign of returns of last three days predicts the sign of an upcoming return with quite a significant accuracy. However, the sign of return tends to change after 9-10 days, which hints on mean-reverting after two weeks.

[5] The confidence interval is given by a formula$[\mu - z_{\frac{\alpha}{2}} * \sqrt{\frac{p(1-p)}{n-1}}; \mu + z_{\frac{\alpha}{2}} * \sqrt{\frac{p(1-p)}{n-1}}]$, where α is the confidence level, $z_{\frac{\alpha}{2}}$ is the inverted standard normal distribution function, and p is the expected probability of one time event, in our case 50 percent. For further details see (Greene, 2003), (Daniel, 1995)

The same trend is seen on futures return, but on much lower probability levels that does not allow us to state statistical significance. Only if the futures return was positive one day before, there is a slight indication that the positive return will follow. Moreover, for negative returns, the probability values are closer to lower bound of confidence interval, indicating that it is more likely that the return will become positive after the appearance of negative one in previous days.

Therefore, although there is a strong trend in the spot market, in the futures market of iron ore the returns tend to be much more fluctuating and not following trends, especially when the prices are downward directed.

Figure 8 - Autocorrelation of futures daily positive returns

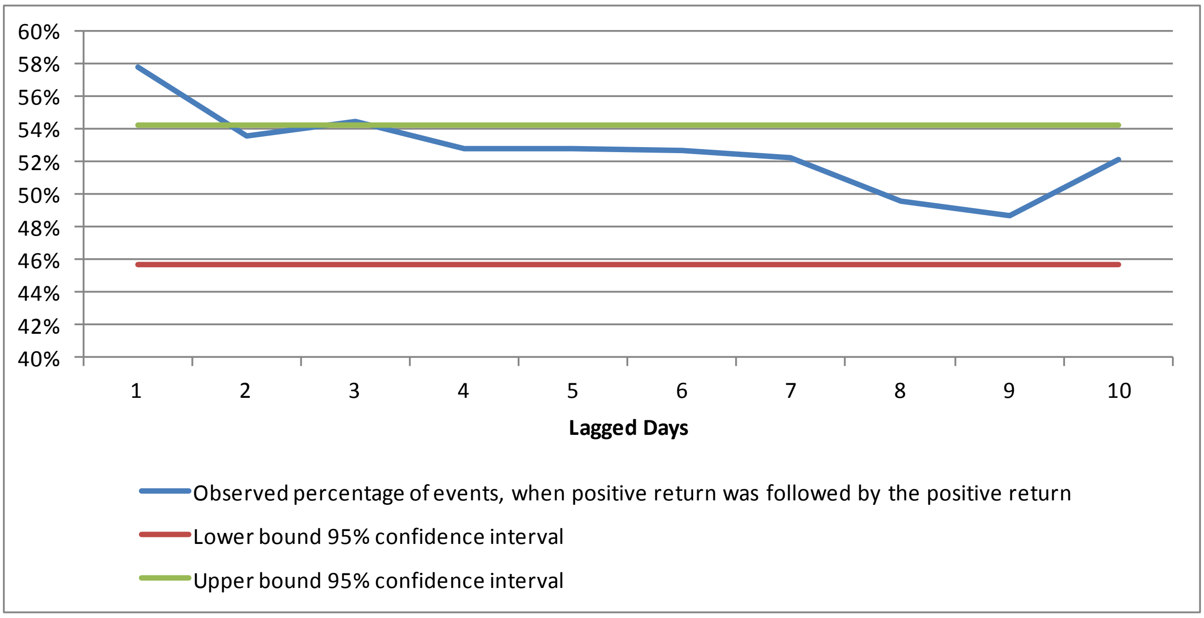
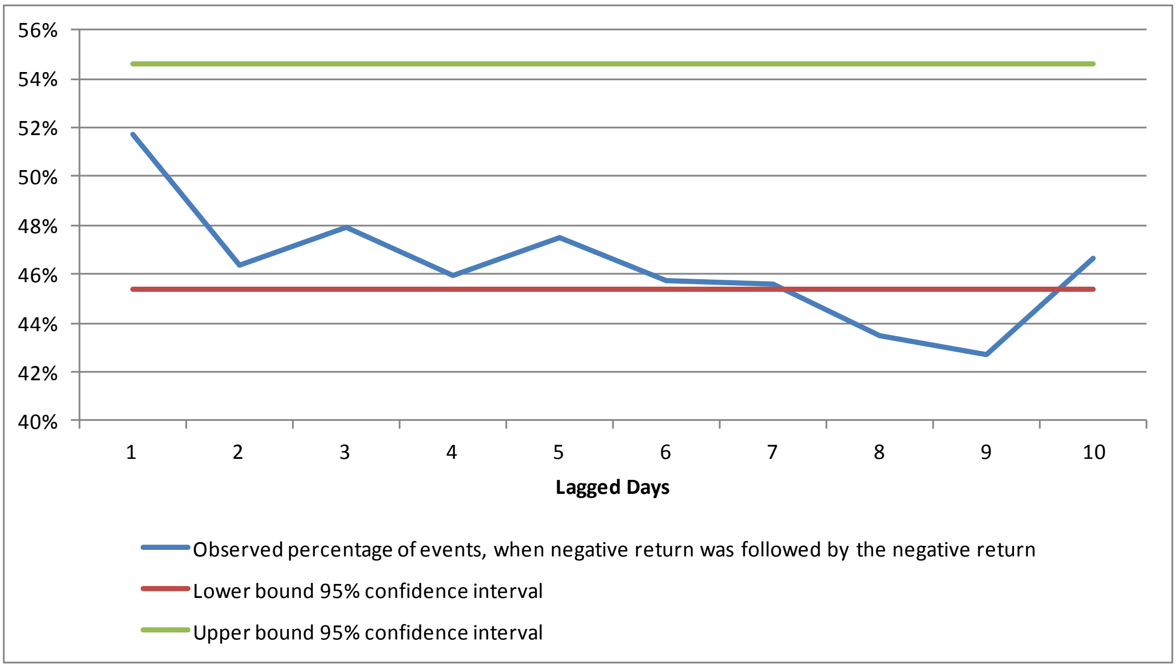


Figure 9 - Autocorrelation of futures daily negative returns



The same type of analysis but with weekly returns was implemented for futures to reveal traces of trends if any (see Figure 10 and Figure 11).

Figure 10 - Autocorrelation of futures weekly positive returns

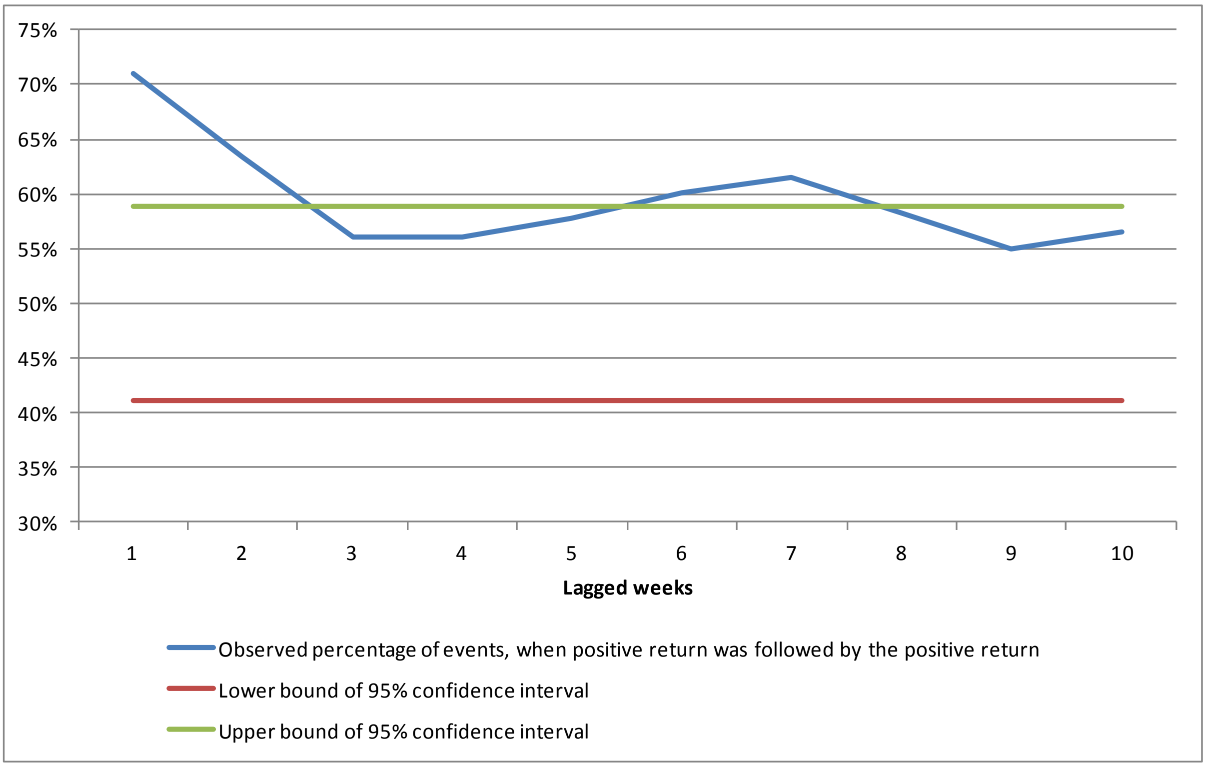
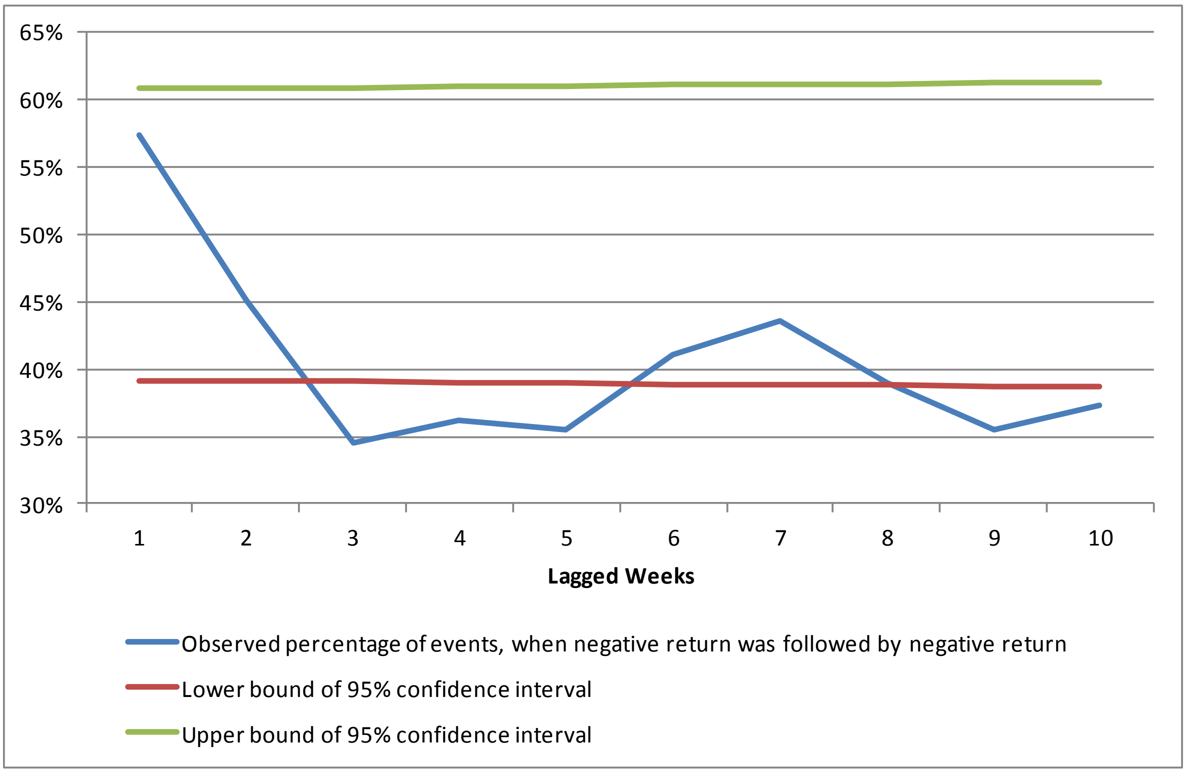


Figure 11 - Autocorrelation of futures weekly negative returns



The conclusions are the same. If the return is positive it is likely to stay the same, although only the latest week return is statistically powerful enough to assert the statement, whereas for negative returns the opposite seems to be true, negative returns are reverted back.

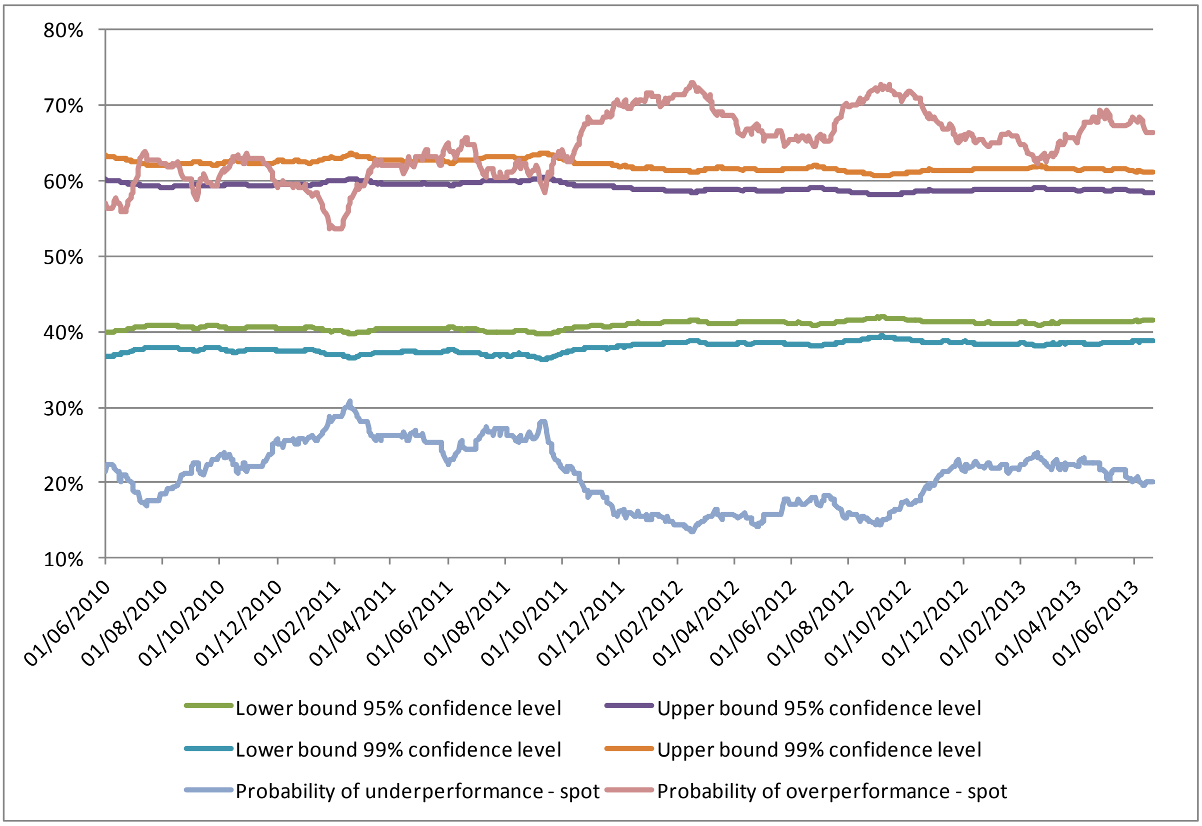
7. Consistency of the momentum effect over time

Another interesting question is how the phenomenon changed throughout the time. To test the dynamics we propose a generation of theoretical trading strategy. The assumption is that both spot and futures can be bought long or sold short without transaction costs. The assumption is not realistic for spot market, but for the purpose of the test it is acceptable.

The trade has the following algorithm. If in prior day the return is positive (negative), buying (selling) of the position is initiated. We will call this trading algorithm momentum trading, because it can be one of the variations of trade based on time-series momentum. Each day the theoretical return of the trade is compared to the return that of passive benchmark, which is the simple long position in the corresponding spot or futures market.

If the price movements are random, the probability of outperformance (underperformance) of the momentum strategy is purely by chance and therefore should be around 50 percent. Performance of initiated algorithm is calculated by counting the number of outperformance and underperformance events, and then the ratio of outperformance and underperformance calculated based on the number of trades done within 250 trading days. These shares are calculated again in each consecutive trading day using the last 250 day data and dragged across the time to assess the consistency of the ratios (see Figure 12). The confidence intervals are calculated using the same approach described for testing autocorrelation of return directions. The difference is that the varying number of events (selling or buying orders) happening during last 250 trading days changes the confidence intervals slightly over time.

Figure 12 – Probability of momentum strategy to over and underperform passive long only strategy for iron ore spot market based on one year rolling observations

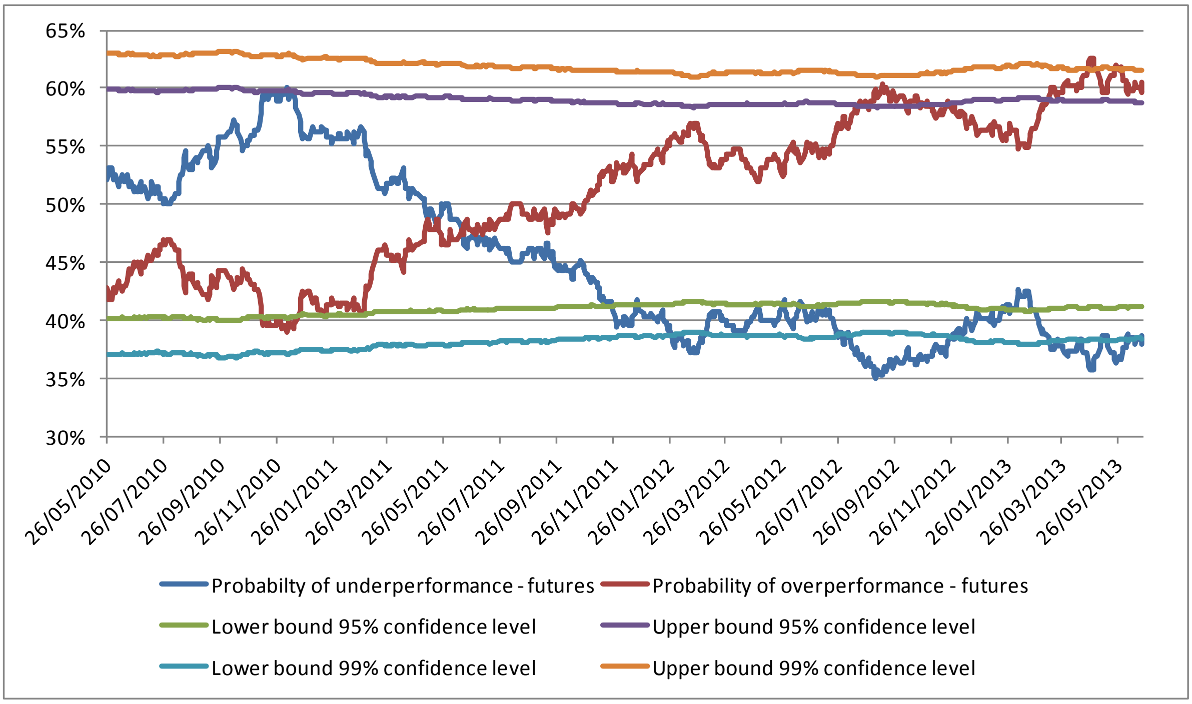


For the spot market the probability of outperformance of offered momentum strategy ranges from 55 to 73 percent, while the probability of underperformance is low and in a range from 8 to 32 percent. Almost for the whole period both phenomena were statistically significant with 95 percent confidence level, and in most cases with 99 percent confidence level.

Note that both underperformance and outperformance compared to passive long only position can happen only when the position in the underlying is short, because otherwise the portfolio will imitate the passive one, and above or below benchmark return cannot happen by definition.

The results of the same analysis on futures are depicted in Figure 13.

Figure 13– Probability of momentum strategy to over and underperform passive long only strategy for iron ore futures market based on one year rolling observations

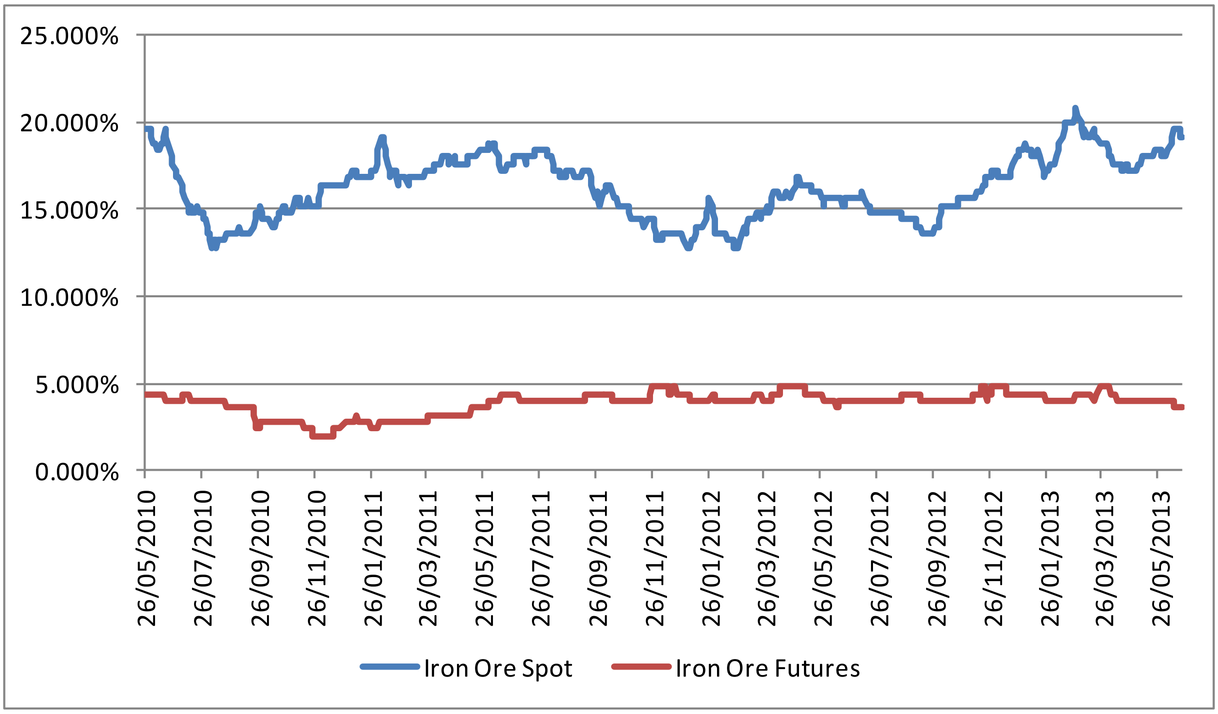


First, you can see from Figure 13 that the probability of outperformance was below 50 percent until the beginning of 2011, when the trend changed and came closer to the picture we see in the case of spot returns.

Second, you will notice high correlation between probabilities of outperformance of the same trading algorithm in spot and futures market. The correlation coefficient equals to 80 percent.

One challenge with the analysis above is that we assumed that prices should move either higher or lower, and our portfolio will either outperform or underperform. However, the iron ore futures market cannot be compared to the currency markets with the level of liquidity and days without price moves happen from time to time. In Figure 14, you can see the share of trading days, when prices did not move. The good news is that the share is fairly constant over time both for spot and futures market and will not affect the analytical steps described above.

Figure 14 – Share of zero returns – one year moving average



8. Time-Series Momentum: Statistical Approach

So far we identified correlation between the sign of past returns and future returns in iron ore spot market, while in futures market the correlation was weak and not consistent over time.

In a paper (Maerkowitz, 2012), authors were examining time-series momentum across variety of stock, bond, currency, and commodity futures markets from 1985 to 2010 in 58 liquid instruments. They found persistence in returns for the first 12 months and then partial reversal over longer horizons, consistent with behavioral theory explanation. Diversified portfolio of time series momentum strategies across all asset classes delivered substantial abnormal returns with little exposure to standard asset return factors described by Fama-French model.

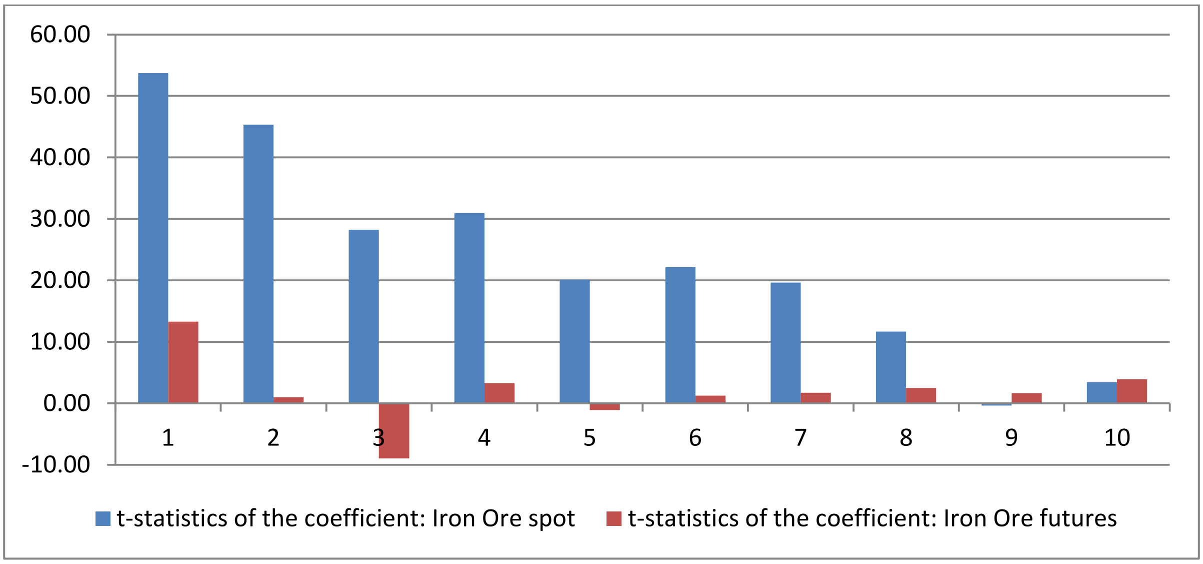
In the paper authors tested the hypothesis of existence of time series momentum by regressing lagged returns with future returns and changed the lagged returns to see which lagged variable explained the future return the most. The authors suggested scaling returns by the exponentially weighted average volatility to make them comparable across all asset classes. The equations had the following form.

$$x(t) = \alpha_0 + \alpha_1 x(t-k) + \epsilon_t, \quad k = 1, \dots, n \qquad \text{(Eq. 1)}$$

In the equations seen in the figures, $x(t) = r(t)/\sigma(t)$, where ex-ante annualized variance is calculated as follows $\sigma(t)^2 = 261\sum_{i=0}^{\infty}(1-\delta)\delta^i(r(t-1-i)-\bar{r}(t))^2$, where $r(t)$ is the return, $\bar{r}(t)$ is the arithmetic average return and δ is such that the centre of mass of the weights is equal to 60 days $\sum_{i=0}^{\infty}(1-\delta)\delta^i = \delta/(1-\delta)$ =60. The centre of mass of the weights shows the average duration of the market memory to volatility shock. The longer the duration, the closer the discounting parameter will be to one, which will increase the relative weight of more distant volatilities. In particular case, the correct approach to estimate δ would require empirical checks to see what the historical memory for the market is and if that memory is consistent, use that estimate. Due to the lack of implied volatility data, we take the same value, offered by the authors for the general population of asset classes.

A similar procedure is performed in this paper on iron ore spot and futures returns. The t-statistics of the coefficients of different equations with varying lags are depicted in the Figure 15. The values on horizontal axis are the lagged days, and the values of vertical axis are the t-statistics of corresponding equations. Values with absolute values above 1.96 indicate 95 percent statistical significance. For all equations of spot returns with lagged variables up to 8 days the coefficients were statistically significant. For equations describing futures returns the magnitude of significance is strong for the first day, but then disappears for the second day.

Figure 15 – t-statistics of dependent variable's coefficients: Iron ore spot and futures



It is apparent that for spot price returns the lagged variables have very significant statistical significance, which declines as we take independent variables more distant ones, and starting from second to third week there is a tendency of mean reversion.

For futures, the momentum is much weaker, the first day-lagged variable is significant, but the other lagged variables are mostly not significant or indicate to the reversion of trend.

9. Time-Series Analysis of Iron Ore Spot Returns

9.1 Unit Root and Autocorrelation Tests

The method to identify momentum offered by (Maerkowitz, 2012) lists several regressions with only one independent variable. In our case, when we have only one commodity index, it is more preferable to identify time-series equation, which will be the best fit for the data and perform well in out of the sample test.

We start from analysis of iron ore spot market. First of all we need to make sure that the returns are stationary in order to continue with any time series analysis. The unit root test performed on the returns of the iron ore spot is seen in Table 4. The aim of this test is to ensure that the time series of returns does not exhibit any trends.

Table 4 - Unit Root Test for spot returns

Null Hypothesis: R_SPOT has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-23.37829	0.0000
Test critical values:	1% level	-3.967035	
	5% level	-3.414208	
	10% level	-3.129215	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000162
HAC corrected variance (Bartlett kernel)	0.000240

The probability of the existence of unit root is basically zero and we can continue to further explore the data.

The returns exhibit significant autocorrelation, which are depicted in Table 5, which violates the assumptions of classical least liner regression model.

Table 5 - Autocorrelation for spot returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.390	0.390	156.51	0.000
		2	0.297	0.171	247.43	0.000
		3	0.202	0.048	289.48	0.000
		4	0.185	0.069	324.95	0.000
		5	0.168	0.057	354.18	0.000
		6	0.141	0.026	374.64	0.000
		7	0.116	0.015	388.65	0.000
		8	0.053	-0.044	391.51	0.000
		9	-0.045	-0.115	393.56	0.000
		10	-0.001	0.024	393.56	0.000

9.2 The Model

We saw that although the returns are stationary, they are not immune to autocorrelation. That is why all equations discussed will be generalized autoregressive conditional heteroskedasticity models (GARCH)[6].

Let us begin with the simple one with the following specifications

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \epsilon_t \qquad \text{(Eq. 2)}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \qquad \text{(Eq. 3)}$$

Where $s(t)$is the spot return at time t, $\varepsilon(t)$ is the error term, and σ_t^2 is the variance.

The first equation regresses current return with the return of the previous day. The second equation is for control of non-stationary variance of errors. As the returns of iron ore are very volatile with constantly changing volatility regimes, the second equation is necessary to escape the problem with non-stationary variance.

In order to test out-of-sample performance of the models, we took only first half of the observations that are from 1st of June 2009 up to 1st of June 2011. The characteristics of the regressions are given in Table 6. All coefficients of independent variables are statistically significant and adjusted R-square of the model is 9.5 percent. Note that the coefficient of the lagged variable is positive and equal to 0.437, which can be interpreted that for each

[6] For more on GARCH and other models of time series variance see (Hamilton, 1994)

additional 1 percent of the lagged return the next day return is going to increase by 0.437 percent.

Table 6 - Regression Output of equation 2 and 3

Sample (adjusted): 6/03/2009 6/01/2011
Included observations: 504 after adjustments
Convergence achieved after 28 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001504	0.000829	1.813292	0.0698
AR(1)	0.437060	0.051217	8.533536	0.0000
		Variance Equation		
C	6.65E-07	3.56E-07	1.867387	0.0618
RESID(-1)^2	0.067058	0.011870	5.649376	0.0000
GARCH(-1)	0.929070	0.010070	92.25840	0.0000

R-squared	0.097235	Mean dependent var	0.001967
Adjusted R-squared	0.095437	S.D. dependent var	0.013220
S.E. of regression	0.012573	Akaike info criterion	-6.139755
Sum squared resid	0.079359	Schwarz criterion	-6.097865
Log likelihood	1552.218	Hannan-Quinn criter.	-6.123323
Durbin-Watson stat	2.417784		
Inverted AR Roots	.44		

9.3 Checks for Correct Specification and Model Adjustments

However, the model is not specified correctly, as the residuals are serially correlated as it is seen in residual autocorrelation test in Table 7. P-values are near zero indicating strong residual autocorrelation.

Table 7 - Q-statistics residual test of equation 2 and 3

Sample: 6/03/2009 6/01/2011
Included observations: 504
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.120	-0.120	7.2876	
		2	0.134	0.121	16.382	0.000
		3	0.126	0.159	24.410	0.000
		4	0.099	0.122	29.389	0.000
		5	0.127	0.125	37.578	0.000
		6	0.029	0.017	38.004	0.000
		7	0.057	0.001	39.645	0.000
		8	0.076	0.034	42.637	0.000
		9	-0.013	-0.042	42.725	0.000
		10	-0.001	-0.055	42.725	0.000

When we add more lagged variables to the autoregressive model, adjusted R-Square improves, while the coefficients remain statistically significant up to third lagged variable.

The second model equation 4 and 5 and third model includes equations 6 and 7.

They are following:

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 s_{t-2} + \epsilon_t \qquad \text{(Eq. 4)}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2, \qquad \text{(Eq. 5)}$$

$$s_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 s_{t-2} + \alpha_3 s_{t-3} + \epsilon_t \qquad \text{(Eq. 6)}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2, \qquad \text{(Eq. 7)}$$

The regression output of the second model is in Table 8 and the regression output of the third model is in Table 9.

Table 8 - Regression output equations 4 and 5

Sample (adjusted): 6/04/2009 6/01/2011
Included observations: 503 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001370	0.001086	1.261705	0.2071
AR(1)	0.323932	0.053666	6.036036	0.0000
AR(2)	0.247223	0.048112	5.138463	0.0000
		Variance Equation		
C	5.17E-07	2.79E-07	1.852119	0.0640
RESID(-1)^2	0.048004	0.009777	4.910004	0.0000
GARCH(-1)	0.945646	0.009204	102.7425	0.0000

R-squared	0.159135	Mean dependent var	0.001968
Adjusted R-squared	0.155771	S.D. dependent var	0.013233
S.E. of regression	0.012159	Akaike info criterion	-6.198346
Sum squared resid	0.073918	Schwarz criterion	-6.148001
Log likelihood	1564.884	Hannan-Quinn criter.	-6.178596
Durbin-Watson stat	2.217406		
Inverted AR Roots	.68	-.36	

Table 9 - Regression Outputs equations 6 and 7

Sample (adjusted): 6/05/2009 6/01/2011
Included observations: 502 after adjustments
Convergence achieved after 40 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001217	0.001206	1.008571	0.3132
AR(1)	0.283692	0.053979	5.255600	0.0000
AR(2)	0.208843	0.046330	4.507735	0.0000
AR(3)	0.135855	0.044253	3.069960	0.0021
		Variance Equation		
C	4.10E-07	2.24E-07	1.828815	0.0674
RESID(-1)^2	0.035167	0.007942	4.428053	0.0000
GARCH(-1)	0.957396	0.007613	125.7640	0.0000

R-squared	0.177515	Mean dependent var		0.001959
Adjusted R-squared	0.172561	S.D. dependent var		0.013245
S.E. of regression	0.012048	Akaike info criterion		-6.218152
Sum squared resid	0.072288	Schwarz criterion		-6.159327
Log likelihood	1567.756	Hannan-Quinn criter.		-6.195073
Durbin-Watson stat	2.158674			
Inverted AR Roots	.78	-.25+.34i	-.25-.34i	

There are several observations, while looking at model outputs. First, coefficients remain statistically significant and positive. Second, the coefficients of lagged variables in a monotonous way are decreasing the more distant the lagged variable is, while staying positive. This means that, although continuing to explain the returns, these lagged variables lose the magnitude of influence in line with their distance from the estimated variable. Third, the adjusted R-Square for the model with one lagged variable is only 9.5 percent, for two variable model it is 15.6 percent and for three variable model it is 17.2 percent. When we take additional variables the model starts losing the strength of adjusted R-Squares. R-Squares explain how much of the observed variations of returns can be explained by the model; the higher the value, the better.

However, we should be careful for correct specification of the models as before and run the same autocorrelation tests. The test results are given in Table 10 and Table 11.

Table 10 - Q-statistics residual test of equation 4 and 5

Sample: 6/04/2009 6/01/2011
Included observations: 503
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.052	-0.052	1.3445	
		2	-0.067	-0.069	3.5938	
		3	0.084	0.077	7.1368	0.008
		4	0.085	0.090	10.783	0.005
		5	0.090	0.112	14.904	0.002
		6	-0.005	0.012	14.917	0.005
		7	0.034	0.034	15.507	0.008
		8	0.065	0.046	17.648	0.007
		9	-0.030	-0.038	18.102	0.012
		10	-0.018	-0.033	18.277	0.019

Table 11 - Q-statistics residual test of equation 6 and 7

Sample: 6/05/2009 6/01/2011
Included observations: 502
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.026	-0.026	0.3477	
		2	-0.026	-0.027	0.6952	
		3	-0.018	-0.019	0.8602	
		4	0.079	0.077	4.0252	0.045
		5	0.075	0.079	6.9167	0.031
		6	-0.017	-0.009	7.0637	0.070
		7	0.024	0.030	7.3541	0.118
		8	0.044	0.042	8.3438	0.138
		9	-0.028	-0.037	8.7492	0.188
		10	-0.032	-0.036	9.2899	0.233

For the second model with two lagged variables, there is still some autocorrelation left in residuals, while in the third model the residuals are not prone to autocorrelation; Q-statistics are within acceptable range that is for 95 percent confidence, and we can say that the third model is correctly specified. This is good news, as the last model had the highest adjusted R-Square.

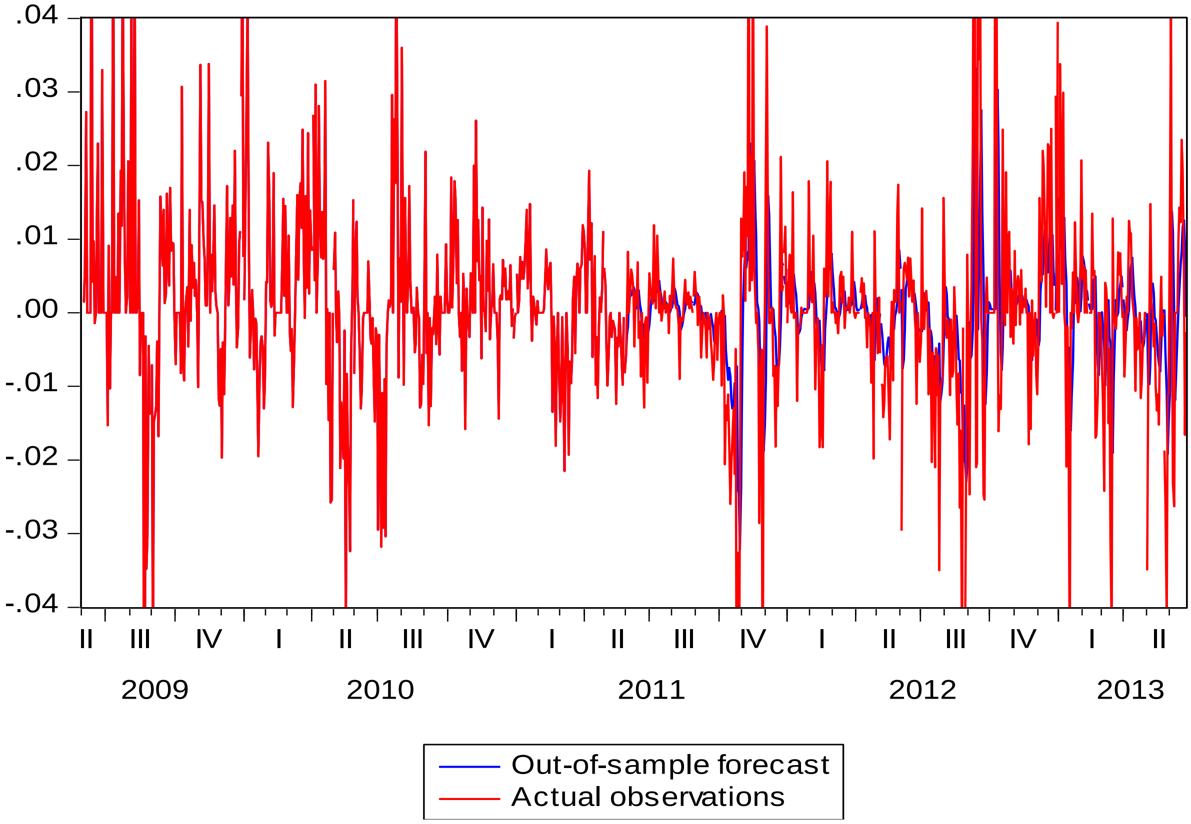
9.4 Out-of-Sample Test

The last critical question waiting for clarification is whether the models can be as good out-of-sample as in-sample. For that purpose we run the models, get the results and then calculate errors comparing with out-of-sample values. Summing the squares of these errors and taking the square root of the sum we will get the root mean squared error (RMSE)[7]. Lower values of RMSE indicate more robust models with better out-of-sample performance. The first model has a value of RMSE 0.012976, the second model – 0.013060 and the third model 0.013240. The difference between them is not substantial; however, as the first two models had residual autocorrelation, the only choice is the third model.

The visual depiction of the forecast against actual values is seen in Figure 16.

[7] For details see (Hamilton, 1994)

Figure 16 - Actual iron ore spot returns and the fitted forecast



To sum up with our results, we can state that past returns have statistical power to explain future returns in iron ore spot market. Moreover, the returns are following trends, that is, they have a momentum effect. Last three days of returns are positively correlated with the current return and GARCH model using these lagged days' returns as independent variable can be used as a short term forecasting tool. The biggest share of explanatory power has the previous day return.

10. Time-Series Analysis of Iron Ore Futures Returns

10.1 Data Adjustments, Unit Root, and Autocorrelation Tests

Now let us turn our attention to iron ore futures. Again, we want to test whether past returns have explanatory power. We take half of the data from 1st of June 2009 to 1st of June 2011.

The daily data of monthly futures prices has one drawback. When the futures contract needs to be changed as the previous one expires, there is a spike in daily returns not comparable with its magnitude to the ordinary daily fluctuations. From one hand, these spikes due to rollover effect may explain a majority of returns. On the other hand, their existence in the data set will complicate the analysis by introducing strong noises. In academic literature, where the futures are examined the data is generally larger and with monthly intervals. Thus, the problem of monthly rollovers was missing there.

We begin by setting the beginning of month returns equal to the previous day return. All other things constant, the changed data would indicate a stronger momentum effect, if any. If the null hypothesis of existence of momentum return is rejected on this data, it would be rejected on the initial data, too.

The steps for classical time series analysis are the same as for spot returns. First, the stationarity of returns is tested. The results are in Table 12.

Table 12 - Unit Root Tests for Futures Returns

Null Hypothesis: R_FUTURES has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-27.83805	0.0000
Test critical values:	1% level	-3.967044	
	5% level	-3.414212	
	10% level	-3.129218	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	9.70E-05
HAC corrected variance (Bartlett kernel)	9.20E-05

Like spot returns, futures returns do not exhibit any trends, and can be tested further. The next test is for autocorrelation (see Table 13)

Table 13 - Autocorrelation for futures returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.137	0.137	19.198	0.000
		2	-0.021	-0.041	19.665	0.000
		3	-0.032	-0.024	20.700	0.000
		4	0.024	0.032	21.318	0.000
		5	0.055	0.046	24.433	0.000
		6	-0.022	-0.036	24.921	0.000
		7	0.038	0.052	26.445	0.000
		8	-0.014	-0.027	26.653	0.001
		9	-0.055	-0.053	29.811	0.000
		10	0.010	0.027	29.921	0.001

10.2 The Model

Despite of much smaller scale there is still autocorrelation in returns, therefore as before GARCH models are necessary to model time series.

$$f_t = \alpha_0 + \alpha_1 f_{t-1} + \epsilon_t \qquad \text{(Eq. 7)}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \epsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \qquad \text{(Eq. 8)}$$

Equations 7 and 8 are similar to equations 1 and 2. The only difference is that instead of s_t- spot returns we have f_t - futures returns, and ϵ_t - error term and σ_t^2 - volatility are of futures returns.

The regression output is given in Table 14.

Table 14 - Regression Output Equations 7 and 8

Sample (adjusted): 6/03/2009 6/01/2011
Included observations: 504 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001396	0.000382	3.657717	0.0003
AR(1)	0.103180	0.056863	1.814534	0.0696
		Variance Equation		
C	2.92E-05	3.94E-06	7.402773	0.0000
RESID(-1)^2	0.307243	0.060973	5.039004	0.0000
GARCH(-1)	0.418760	0.066265	6.319449	0.0000

R-squared	-0.001154	Mean dependent var	0.001726
Adjusted R-squared	-0.003149	S.D. dependent var	0.010114
S.E. of regression	0.010130	Akaike info criterion	-6.516003
Sum squared resid	0.051515	Schwarz criterion	-6.474112
Log likelihood	1647.033	Hannan-Quinn criter.	-6.499570
Durbin-Watson stat	2.079113		
Inverted AR Roots	.10		

The regression output shows that the lagged return does not have statistical significance and the explanatory power of the model given by adjusted R-Square is zero.

Moreover, adding new lagged variables did not improve the picture. Therefore, for futures returns at least for the given period, the momentum behavior is missing. In the previous chapter the analysis of momentum strategy was performed and we have seen that in futures market the strategy started working better at the end of the total data set. This observation is confirmed by the regression analysis that we do on the second part of the data set that was left for out-of-sample test. The second part comprises of daily observations from 2nd of June 2011 to 24th of June 2013. Using the same equation 7 and 8 a different regression output is generated (see Table 15).

Table 15 - Regression Output Equations 7 and 8: Period 02/06/2011 - 24/06/2013

Sample (adjusted): 6/02/2011 6/21/2013
Included observations: 519 after adjustments
Convergence achieved after 113 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000536	0.000486	1.102827	0.2701
AR(1)	0.166962	0.073843	2.261033	0.0238
		Variance Equation		
C	2.02E-05	3.47E-06	5.821294	0.0000
RESID(-1)^2	0.321681	0.066086	4.867586	0.0000
GARCH(-1)	0.502049	0.079801	6.291264	0.0000

R-squared	0.045153	Mean dependent var	0.000420
Adjusted R-squared	0.043306	S.D. dependent var	0.009782
S.E. of regression	0.009568	Akaike info criterion	-6.672479
Sum squared resid	0.047330	Schwarz criterion	-6.631517
Log likelihood	1736.508	Hannan-Quinn criter.	-6.656431
Durbin-Watson stat	1.842732		
Inverted AR Roots	.17		

In this period the lagged variable is statistically significant and adjusted R-Square is 4.3 percent. The residuals do not have autocorrelation (see Table 16).

Table 16 - Q-statistics residual autocorrelation test for futures

Sample: 6/02/2011 6/21/2013
Included observations: 519
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.046	0.046	1.1038	
		2	-0.011	-0.014	1.1714	0.279
		3	0.029	0.030	1.6165	0.446
		4	-0.008	-0.011	1.6529	0.647
		5	0.025	0.027	1.9880	0.738
		6	0.001	-0.003	1.9882	0.851
		7	0.066	0.068	4.2815	0.639
		8	0.052	0.045	5.7352	0.571
		9	-0.078	-0.080	8.9266	0.349
		10	0.005	0.009	8.9404	0.443

Additional lagged variables do not add an explanatory power to the model. So, for iron ore futures the results are mixed. Even if there is a momentum, it is a recent phenomenon and short span of time casts significant doubt on its consistency over time.

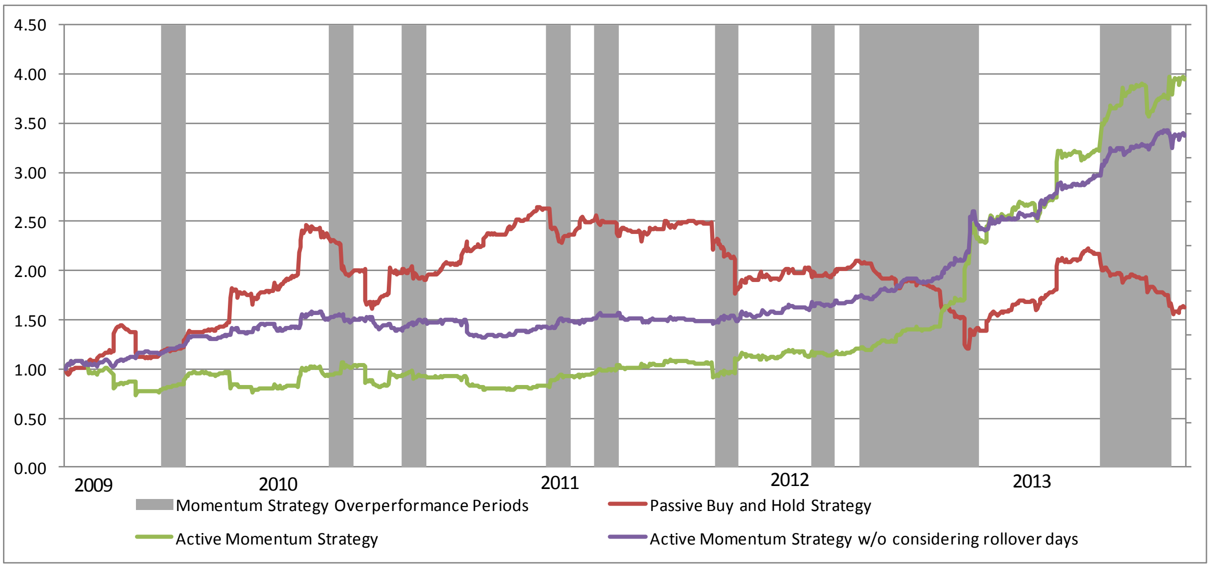
11. Trading Algorithm

So far, the evidence of momentum behavior in the futures market was mixed. If there is some trending, it would be interesting to know whether in practice these trends can be exploited profitably.

Due to the fact that the simplest time series equation with only one lagged variables was the best fit for futures data, we will model and back-test the trading algorithm based on that equation. The trading mechanism is simple; if the market moved upwards in previous day, buy the future contract and be in a long position, if the market moved downward sell the future contract and be in a short position. When the position is long, the portfolio will benefit from the market's positive returns, while when the position is short, the portfolio will benefit from the market's negative returns. In cases when the market continues to be in a bull or bear sector no trade is initiated and the position is kept either long or short. Simultaneously, another portfolio is kept for the benchmark that is the long-only position of the futures.

The trade is initiated at the beginning of the period and cumulative return is calculated. At the end of the period this cumulative return is compared to the cumulative return of the benchmark. The results of the initiated algorithm are given in Figure 17. Besides standard futures return, the same steps were done for the returns where the monthly rollover effects were eliminated. For each month there is a check to see whether that month momentum strategy outperformed passive buy-and-hold strategy or not, if there is an outperformance that period is shaded by the grey color.

Figure 17 - Trading with no transaction costs



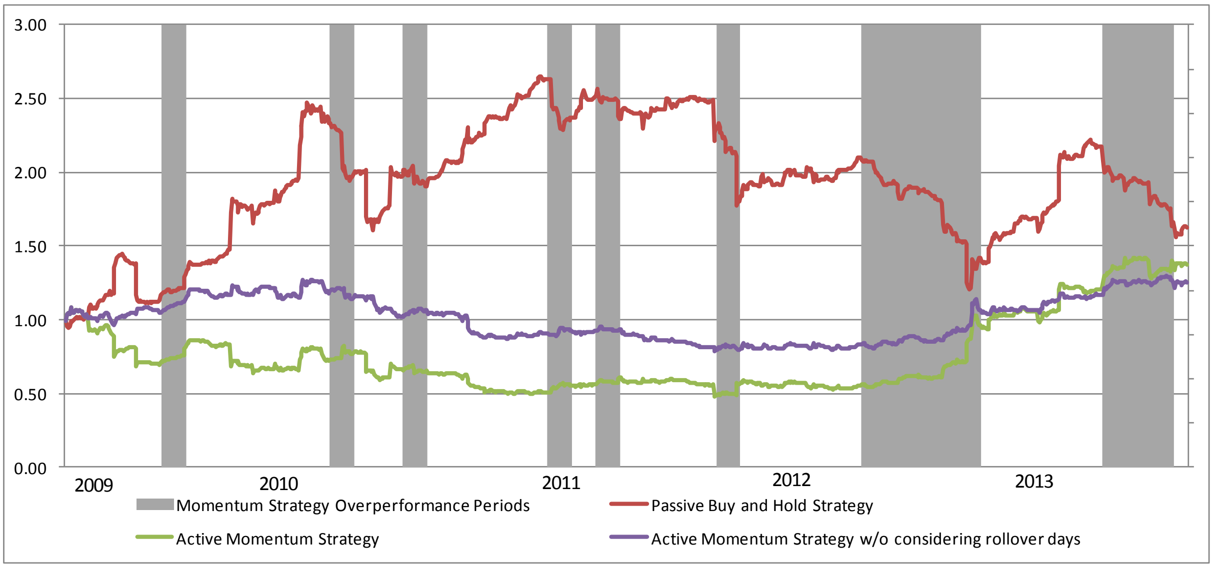
You can see that momentum strategy outperformed buy-and-hold strategy and gave annualized return of 40 percent compared to the 13 percent of the benchmark. This sounds very significant outperformance, however the trade was risky, as the momentum strategy was behind until the end of 2012. Unfortunately, we cannot measure the riskiness of the trade in terms of traditional portfolio theory, and its correlation with standard systematic risk factors, where the return is regressed against several risk factors to assess the diversification benefit of active momentum portfolio and its possible above-average risk-adjusted return. Risk factors can be market risk, liquidity risk, and inflation risk, or risk factors of traditional Fama-French model[8], which are market risk, market capitalization factor, and price to book ratio. The drawback of our data not allowing us to do so is the shortness of data and its daily frequency, which adds noise.

[8] For details see (Fama, 1993)

12. Discussion of Factors Affecting the Profitability of the Trade

When we run the trading algorithm, we assumed frictionless market without transaction costs and information asymmetry. In Singaporean Stock Exchange the usual transaction cost is 0.25 percent. Big players can get half of it, therefore changing a position from long to short or vice versa require 0.25 percent from big players. That figure is taken to assess the illiquidity effect on momentum trade. When this effect is added the picture changes and instead of 40 percent annualized return, the trade generates only 8 percent annualized return. Passive benchmark does not accrue any transaction costs and therefore keeps 13 percent performance, which is higher than 8 percent. The visual representation of the trade with transaction cost is depicted in Figure 18.

Figure 18 - Trading with 0.25 percent transaction cost



The result tells that even big players would not be able to profit from this strategy, although the periods of outperformance brushed with the grey area were still significant.

Another risk is that during the most volatile periods, when the majority of profit can be realized, and the frequency of trades to keep momentum strategy increases, the liquidity can evaporate from the market. The mechanism is simple, when the market crashes, market participants become loss averse, as they try to squeeze the ballooned volatility of their portfolio and fall into behavioral bias trap trying to eliminate the losses as soon as possible, the consequence is the increased demand of trade and a flow of sell orders, meanwhile potential buyers disappear from the market. This amplifies the problem and the market continues to fall. The same thing can happen, when the market is in sharp upward, especially when the short selling is widespread as in futures market. Decreased liquidity during increased volatility periods can significantly alter the performance of paper portfolios with real ones.

13. Possible Topics for Further Research

Having examined the regressions both for iron ore spot and futures returns we found that spot returns have a significant serial correlation and the returns are prone to momentum, whereas for futures, the momentum is present only in the second half of the data that begin from June 2011.

These findings are interesting and feed several questions. First, what was behind the change of price patterns in futures market? Is that contributed to the change of market participants, particularly smaller activity of speculators? Second, how the parameters of the market, such as liquidity characteristics: bid-ask spreads, trade volume, and the number of participants affect the momentum behavior. Third, how the market fundamentals, such as inventory levels and transportation costs affect the momentum behavior? Fourth, it would be interesting to see whether for other commodity markets there is still such relation, when spot markets are much less weak-form efficient with higher autocorrelation than futures markets. Fifth, how are the autocorrelation changes when the frequency of return observations was lower, such as for monthly data?

14. Conclusion

We find significant momentum returns in iron ore spot market. The GARCH model with three lagged variables that represented daily returns from 2009 to 2011 has adjusted R-square of 17.25 percent. Out-of-sample test shows that the model continues to have an explanatory power outside the predetermined data set.

In iron ore futures market the returns do not exhibit momentum, at least in the given sample. The autocorrelation of returns increases over time and in the second half of the data from 1st June 2011 to 24th June 2013 period, momentum in returns is present. However, the explanatory power is in much smaller scale compared to the explanatory power of the model for spot returns and is around 4.5 percent.

To eliminate the uncertainty in a question whether there are momentum returns in iron ore futures market, we generated a trading strategy that tries to reap the benefit of momentum, if any. We find that the strategy is profitable assuming no transaction costs, but the profitability disappears after considering realistic transaction costs.

15. References

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