DOUBLE-SORT TRADING STRATEGY ON COMMODITY FUTURES: PERFORMANCE EVALUATION AND STOP-LOSS IMPLEMENTATION

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ABSTRACT

This master thesis, first, re-examines the performance of the double-sort trading strategy on commodity futures using the data from January 1979 to October 2011. The double-sort strategy is an active strategy that uses momentum and term-structure signals to form a long-short portfolio of commodity futures. Second, the performance of the strategy is studied before the beginning of the financial crisis at 2007 and compared to the performance of the strategy during the crisis, i.e. after 2007. We find that the strategy performs better during the crisis. Third, in an effort to reduce the risk measures of the strategy, stop-loss methods are introduced and added to the strategy. Four different stop-loss methods are implemented: cumulative, exponentially weighted average, consecutive, and full-portfolio stop-loss. We find that none of these methods are able to reduce the risk-measures of the strategy considerably.

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1. Introduction

In the last decade, commodity and commodity investment have become popular and a separate asset class for investment purposes. According to a Barclays Capital survey of over 250 institutional investors, commodities institutional investment has risen from $18 billion in 2003 to $250 billion in 2010. Nowadays, commodity market players are not limited to producers and consumers, traditional and alternative asset managers also include commodities in their portfolio more frequently. The existence of commodity risk premium has been at the center of debate since 1930. The attraction of commodity investment lies in different reasons. First, commodities are proven to have equity-like returns. Second, commodities have long been shown to be a natural hedge against inflation. Third, their considerably low correlation with other asset classes such as equities would help make well-diversified portfolios when included in the investment. (See (Bodie & Rosansky, 1980); (Erb & Harvey, 2005); (Gorton & Rouwenhorst, 2004); (Chong & Miffre, 2010); (Baur & McDermott, 2010)). Other more recent researches have shown that commodity futures trading strategies are also capable of generating considerably high returns (Erb & Harvey, 2005) (Miffre & Rallis, 2006) (Basu & Miffre, 2012) (Fuertes, Miffre, & Rallis, 2010). Such strategies mainly employ a combination of signals that are built on the foundation of the two main theories behind the variation of commodity future prices: Storage Theory (Working 1939) and Normal Backwardation (Keynes, 1930). However, long short strategies are based on the hedging pressure hypothesis or the theory of storage - not normal backwardation which implies that investors should be long only. Mainly, momentum, hedging pressure, and term structure signals are used for identifying commodity futures risk premiums and try to build a portfolio that captures such risk premiums. Fuertes, Miffre, and Rallis (2010) use an active strategy that uses both momentum and term structure signals to build a profitable trading strategy. Using the data from 1979-2007, they prove the long-short portfolio resulted from the strategy generates abnormal high returns as high as 23.55%. Such results motivate asset managers to include this strategy in their portfolio. However, the global economy has experienced a strong downturn since 2008 due to first, the sub-prime crisis and now, the credit crisis. Some may argue that the significant high returns of such strategies would fade during a global economic turbulence. Thus, it would seem necessary to verify that whether the strategy is still capable of generating such results in years after 2007. The result of such comparison would also shed light on the performance of such strategies in different market conditions using real market data. Therefore, this study at first re-implements and re-examines the performance of the double-sort strategy using a dataset from 1979 to 2011.

Moreover, although the double-sort strategy (Fuertes, Miffre, and Rallis, 2010) has high risk to reward ratio, it would prove useful to try to decrease the absolute risk measures such as volatility and value at risk, which are nominally high. This study adds four different *stop-loss* methods to the double-sort strategy in an effort to achieve this goal. Different criteria are used to implement the stop-loss methods.

The rest of the paper is structured as follow: Chapter 2 reviews the existing literature on commodity markets and commodities investment strategies. Chapter 3 presents the methodology and results of the double-sort strategy and compares the performance of the strategy on pre and during crisis eras. In chapter 4, the stop-loss method is introduced and results of the four different stop-loss methods are discussed. Chapter 5 summarizes and concludes the findings.

2. Literature Review

2.1 Commodity Futures Market

There are currently two related but separate major markets in which commodities are traded; the spot market (cash market) and the futures market. In the spot market physical commodities are bought and sold and the exchange of the product occurs at the same time that the transaction occurs. In contrast, in futures market *future obligations* are traded. The future contract obliges the participants to make or take delivery at some date in future (Garner, 2010).

2.2 Relationship between spot and future price

The future contracts prices on commodities are almost always different from their spot price. Two major theories are available to explain this variation: storage theory and normal backwardation theory. The two theories date back as far as 1930.

2.2.1 Storage theory

Due to cost of storage and delivery, the spot price is normally different from the futures price. Naturally, as the cost of storage cannot be negative, the spot price of a commodity would be cheaper than its futures price. Based on the same reasoning, the near-month expiring future contracts would be cheaper than the distant-month expiring future contracts. This normal market condition is generally known as *contango* (Figure 1).

However, in reality, it is observable that sometimes the spot price of a commodity is higher than its future price. Explaining this phenomenon with delivery and storage costs is not straightforward. To resolve this issue, Kaldor (1939) has introduced the concept of *convenience yield*. The implicit revenue associated with stock holding is a simple definition of the convenience yield (Lautier, 2009):

> *"In normal circumstances, stocks of all goods possess a yield, measured in terms of themselves, and this yield which is a compensation to the holder of stocks, must be deducted from carrying costs proper in calculating net carrying cost. The latter can, therefore, be negative or positive." (Kaldor, 1939)*

In other words, the usual condition where the price of the futures is higher than the spot price is only true when there is no disruption in the supply. Any shortage in the short-term supply would naturally push the spot prices higher than the futures price. Consequently, the price tends to fall as we go farther on the term structure curve towards the farther maturity future contracts. This scenario is referred to as *backwardation* (Figure 2).

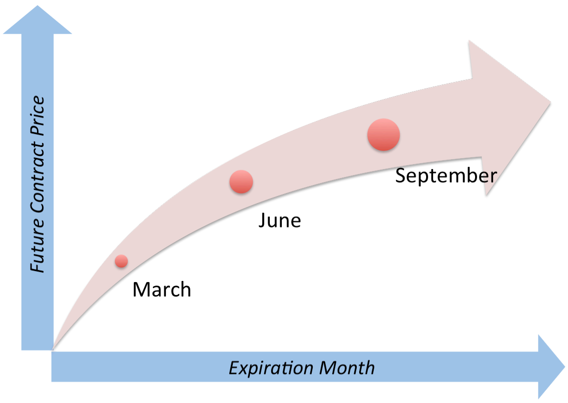

Figure 1 - Contango commodity term structure

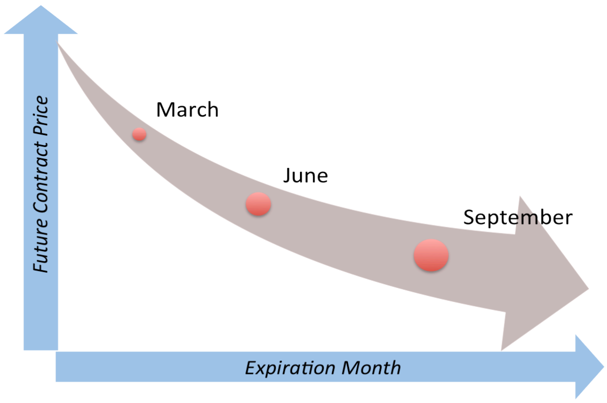

Figure 2 - Backwardation commodity term structure

Two other theories explaining the variations of future prices and their relation to storage and inventories are Working (1949) and Brennan (1958). Working (1933, 1948) has investigated the Chicago's wheat market. He observes that when the difference between spot and futures prices, price of storage, is negative and large, the amount of wheat stored declines. Similarly, the amount stored rises when the price of storage is positive and large.

The graph showing this relationship is known as the *Working Curve* and explanation of the shape of the graph is called *Supply of Storage Theory* (Working, 1949).

Brennan and Williams (1989), Benirschka and Binkley (1995), and Brennan, Williams and Wright (1997) challenge Working's argument that convenience yield results in negative carrying charges. These authors propose that the data aggregation creates the Working curve. Specifically, it is possible that for market reporting purposes stocks of commodities may be aggregated across different qualities and physical locations. Therefore during backwardation, there should be no sign of holding stocks, after stocks and prices are measured for the associated quality and physical location.

Moreover, as Brennan (1958) stated, one would have the opportunity to profit from a sudden increase in demand, if they hold inventories:

> *"The convenience yield is attributed to the advantage (in terms of less delay and lower costs) of being able to keep regular customers satisfied or of being able to take advantage of a rise in demand and price without resorting to a revision of the production schedule."*

Empirical tests of the traditional Theory of Storage examine the theory's central assumption utilizing the convenience yield inferred from the (interest-adjusted) basis. Fama and French (1988) and Ng and Pirrong (1994), examine the Theory of Storage's central assumption empirically. They use testable implications of the convenience yield to study the behavior of the spot and futures prices and their volatilities. They use data on metals, and their results are inline with the theory. However, because the inventory data is not used, as they use the futures data, their evidence is indirect. Moreover, when Brennan (1991) and (1994) used inventory data to test that theory, their finding was that the convenience yield is a decreasing and convex function of inventory for some commodities, including metals. There has been more recent evidence on this theory: Dinceler, Khokher and Simin (2005) for Gold, Copper, Crude Oil, and Natural Gas, and Carbonez, Nguyen, and Sercu (2009) for Wheat, Corn, and Oats using weekly data from two different periods, 1885-1935 and 1985-2005.

2.2.2 Normal Backwardation

Why do the commodities futures markets exist in the first place? “The classic economic rationale for futures markets is that they facilitate hedging” (Chang, 1985). Commodity producers have to sell their production, even with a loss. Futures markets allow those who deal in commodities to obtain contracts through which the risk of price change would be transferred to those (speculators) who are willing to take it. Based on Keynes’ (1930) and Hicks’ (1939) theory of normal backwardation, the purpose behind using futures markets for hedgers is that they want to avoid uncertainty and risk. As everything has its price hedgers are willing to pay a significant premium to others who are willing to take the risk, i.e. speculators. This can be looked at as a kind of insurance. Based on Keynes theory the future prices are an estimate, and often not a precise one, of what the spot price will be on the date of the expiration of the future contract. His conclusion is based on the argument that the long (short) speculator profit by not buying a contract from the short (long) hedger unless they buy at a price below (above) the expected spot price in future.

> *“...In normal conditions the spot price exceeds the forward price i.e. there is backwardation. In other words, the normal supply price on the spot includes remuneration for the risk of price fluctuation during the period of production, whilst the forward price excludes this.” (Keynes, 1930)*

However, as opposed to market backwardation, the normal backwardation is not observable[1]. Cootner (1960) and Deaves and Krinsky (1995) note that there is a rather big

[1] “There are two components of market backwardation: the market consensus expected future spot price and a possible risk premium. While it is possible to observe market backwardation, it is impossible to observe normal backwardation because neither the expected future spot price nor the possible risk premium are observable” (Erb and Harvey, 2005)

assumption in Keynes' theory of normal backwardation. Keynes is assuming that hedgers are always long the underlying commodity, i.e. hedgers have the underlying commodity, and by selling the futures contract, they aim to lessen the negative risk of price fluctuations. Therefore, to persuade investors to buy the commodity futures, the future price is expected to rise over time. In this case, if backwardation holds when hedgers are net short the future contracts and contango holds when hedgers are net long future contracts, both backwardated and contango commodities might have risk premium. Bessembinder (1992) examines the return of sixteen nonfinancial futures over the time period from 1967 to 1989. He finds substantial evidence regarding the influence of net hedging on average returns. In other words, on average, the commodities showed positive excess return when the net position of hedgers was short in those commodities whilst commodities showed negative excess return when the net position was long in those commodities.

There have been other researches as an effort to verify normal backwardation theory. These researches show contradictory results and therefore neither confirm nor reject the theory. Dusak (1973), Bodie and Rosansky (1980), Richard and Sudaresan (1981), Bessembinder (1993) use either static or inter-temporal capital asset pricing model to examine the futures' risk premium and all obtained contradictory results. The critiques of the theory say that, first, even if the mentioned premium exists, the chances are that it is not constant and positive. Second, by saying the hedgers are not always net short, they also attack the first assumption of the theory. Empirical studies also show contradictory results: for some commodities and different periods there may also be, an opposite so called, *normal contango*.

Kolb (1992), to test for normal backwardation, looked at 29 different future contracts and stated that 16 commodities had returns that were not statistically significant, 9 commodities exhibited statistically significant positive returns, and 4 commodities had statistically significant negative returns. Thus, he concluded that *normal backwardation is not normal*.

2.2.3 Combining storage and normal backwardation theory

Having stated that neither of the two above theories have been solidly verified and proven the other wrong, there have been efforts, for example Cootner, (1967), Hirshleifer's (1990), and Khan et al. (2008), on combining the two theories to help explaining the different situations in commodities futures markets. The generalized hedging pressure hypothesis of Hirshleifer (1990) relates the viewpoints of Keynes and Working, where hedging pressure is the natural tendency of market participants to be net long (Miffre and Basu, 2009).

Cootner (1960) and Deaves and Krinsky (1995) state that both backwardated and contango commodities could have the risk premium mentioned by Keynes in one scenario. That scenario is that when the net position of hedgers is short we see backwardation and, vice versa, when the net position of hedgers is long we see contango. Bessembinder (1992) found evidence to support this theory. He found that for 16 non-financial commodities, over the time period 1967 to 1989, the hedging pressure (the degree of net hedging) has influenced the returns. On average, commodities that hedgers were net short had positive excess return and commodities that hedgers were net long had negative excess return during the period. De Roon, Nijman and Veld (2000) also provide similar results regarding the existence of risk premium based on hedging pressure of producers and consumers.

Carter and Giha (2007) utilize the statistical data that Working had used originally to re-examine his theory. To eliminate the potential geographical aggregation issues, they only use Chicago stocks. They also take into account the different grades of wheat to eliminate any further possible problems. Supporting the original Working curve's shape while challenging the aggregation arguments' influence on the shape of the curve, they find that wheat stocks were backwardated in a single location.

With respect to Workings original data, their findings are definitive. However, two issues remain. First, it can still be doubted whether the rather old data (1920s and 1930s) can be validly generalized and be used in the current commodity markets. Second issue is the limitation of Carter and Giha's analysis, as they only use the wheat market. They do not provide proof that the wheat market's results can be generalized to other important commodity markets. Since, storage under backwardation has a great influence on commodity storage models, other researches has been done on this subject. (See below for Joseph, Irwin, and Garcia, 2011).

Joseph, Irwin, and Garcia (2011) come up with evidence on stock holding when backwardation holds. Using weekly stock data from KCBOT[2] wheat and CBOT[3] wheat, soybeans, and corn from 1990 to 2010, they investigate the existence of Working curve with spot and future prices. They process the commodities on various markets. They assess, first, the conventional measure of backwardation, future less spot price, and, next, the futures spread measure. They measure against the local stock held at various physical delivery locations. Based on their results, all four commodities that they have tested show signs of storage under backwardation at delivery locations. However, they state identifying the shape of the curve is more complicated.

The results from the analysis of commodities across different markets provide evidence for storage under backwardation at delivery locations for all four commodities. However, they state that exact form of the Working curve is less straightforward to identify.

De Roon, Nijman, and Veld (2000) present a simple model in spirit of Mayers (1976), Stoll (1979), and Hirshleifer (1988, 1989) in which agents face multiple sources of nonmarketable risks. The model implies that future risk premium depends on both own-market and cross-market hedging pressure. They gather empirical evidence from 20 futures

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[2] Kansas City Board of Trade

[3] Chicago Board of Trade

markets and divide them into four groups: financial, agricultural, mineral, and currency. They conclude that after controlling for systematic risk, both the futures own hedging pressure and cross-hedging pressure from within the group significantly affects the future returns. They show that the effects remain significant after controlling for a measure of price pressure and also that hedging pressure also contains explanatory power for returns on underlying asset.

Gorton, Hayashi, and Rouwenhorst (2012) preform a thorough study on commodity future returns. They introduce a simple two-period model that integrates the Theory of Storage and the Theory of Normal Backwardation. Using a dataset on 31 commodity futures and physical inventories between 1971 and 2010, they show that inventory levels affect the basis[4] and risk premium. They preform two tests in order to verify the hypothesis; first they regress the excess return (whose expected return is the risk premium) on lagged inventory levels and second, they show that inventory levels can be used as a signal to form a portfolio. This signal significantly spreads the portfolio returns, with portfolios that contain low-inventory commodities earning higher returns. They also show that price based signals such as futures basis, prior future returns, prior spot returns and spot price volatility reflect the state of inventory and are informative about the commodity futures risk premium. Based on their findings, building a portfolio using commodities with high past returns and relatively high basis outperforms portfolios using commodities with low past return and relatively low basis. Their final contribution is to characterize the behavior of market future markets' participants in response to inventories. Since researches have linked "hedging pressure", measured by the relative size of positions held by producers, to the risk premium, in empirical implementations of the Theory of Normal Backwardation, this contribution could be important. They show that the positions of

[4] The basis is defined as the difference between the current spot price and the contemporaneous futures price.

traders are contemporaneously correlated with inventories and futures prices. However, They find no evidence to support the correlation between these positions and subsequent commodity futures returns.

2.3 Commodity trading strategies, term structure, roll returns, and momentum signals

Term structure, in general, depicts the relationship between prices at different maturities. In commodities, backwardation and contango can be interpreted using the term structure of commodities. Also, the degree of the backwardation and contango can be viewed using the term structure. As stated earlier, an upward sloping term structure of future prices is associated with contango, where the price of the future contract rises as the maturity increases. Similarly, a downward sloping term structure shows backwardation, where the price of the future contact falls as the maturity increases. This introduces possibility to take advantage of the *roll returns*[5].

Jegadeesh and Titman (1993), although not directly connected to commodity investment, examine a variety of momentum strategies and document that strategies that buy stocks with high returns over some period and sell stocks with poor returns over the same time period are profitable. They find that the profitability of these strategies is not due to their systematic risk or to delayed stock price reactions to common factors. Their momentum strategies on stock markets have been adopted by different researches on commodities futures market and are the foundation of momentum signal trading strategies on commodities market. (Erb and Harvey, 2005; Miffre and Rallis, 2006; Fuertes, Miffre, and Rallis, 2010)

Erb and Harvey's (2005) contribution to commodity trading strategies is notable. They put some doubt on the predictability of commodity returns over time. They argue that

[5] "The roll return is defined as the difference between a commodity future's spot return and excess return, and the term structure of commodity futures prices is the driver of the roll return" (Erb and Harvey, 2005).

historically commodity futures have shown performance similar to that of equities. However, over time, the return pattern has changed and therefore the common risk factors are unable to explain the changes over time. They also challenge the inflation hedge property of commodities by saying that the hedge is inconsistent with unexpected inflation. Also, they argue than the weighting allocation of portfolios of commodity futures is the main reason behind historically high average returns of them. As evidence, they say that a portfolio that contains equally weighted commodity futures and contains only long positions would have had a return of 0% over the last 25 years. In contrast, they provide evidence that tactically allocating assets using commodity future contracts would yield distinct benefits. They employ momentum and term structure signals to tactically allocate assets to commodity futures. They conclude that between long-only and tactical allocation strategies, the latter is preferred as it generates higher average returns while having lower risk.

Miffre and Rallis (2006) use momentum and contrarian strategies to build a profitable portfolio of commodity futures. They test for the presence of short-term continuation and long-term reversal in commodity future prices. The momentum strategies are very simple. They buy the commodities that have preformed well in the recent past while sell the commodity futures that have underperformed in the same time period. The contrarian strategies do the exact opposite. They buy the commodity futures that underperformed in the distant past, sell the commodity futures that outperformed. Miffre and Rallis (2006) form a long short portfolio and hold it for periods ranging from 2 to 5 years. To put this differently, they test to see if the short-term price continuation and the long-term mean reversion identified by Jegadeesh and Titman (1993, 2001) and De Bondt and Thaler (1985) in equity markets are observable in commodity futures markets. While the contrarian strategies do not prove profitable, they identify 13 profitable momentum strategies. Momentum strategies being profitable are inline with Erb and Harvey's (2005) findings.

To capture the risk premium of commodity returns, Miffre and Basu (2009) explore a trading strategy on commodities futures market which takes advantage of the hedging pressure. Based on the generalized hedging pressure hypothesis of Hirshleifer (1990), they construct a portfolio in which commodities are selected based on the open interest of either hedgers or speculators. They then combine the two selection methods to form an alternative double-sort trading strategy. Using a cross sectional dataset for 27 commodity futures from 1992 to 2011, their empirical results support the hypothesis that hedging pressure is a systematic factor in determining the commodity futures risk premium, with finding positive and significant risk premiums. They also find a positive relationship between hedging pressure risk premium and the lagged-volatility of equally weighted portfolio of all commodities. Moreover, they find that the hedging pressure risk premiums diversify equity risk better than long-only commodity portfolios. However, this diversification comes at the cost of losing inflation-hedge property of commodities (Bodie and Rosansky 1980; Bodie, 1983). Finally, they report that the hedging pressure risk premiums explain the performance of active commodity strategies better than long-only commodity benchmarks such as S&P GSCI.

Fuertes, Miffre, and Rallis (2010) employ an active double sort strategy that combines the momentum and term structure signals to build a profitable portfolio on commodity futures. They expand on the term structure-only strategy of Erb and Harvey (2005) by analyzing the term structure profits to the roll-return definition, the frequency of rebalancing of the long-short positions and the date of portfolio formation. They also provide an in-depth analysis of the risk, performance, and trading costs of each of the momentum-only, term structure-only and combined portfolios. They find that combining the two strategies, i.e. momentum and term structure, considerably enhances the performance of either of the individual single-sort strategies. They also suggest that these strategies, due to the very low correlation of their return with those of other asset classes, are excellent candidates to increase diversification of portfolios.

2.4 Other Studies

Egelkraut, Woodard, Garcia, and Pennings (2005) look at a different aspect of the portfolio formation; *leverage*. Their work is an extension of previous works that have studied the effects of including commodities in portfolios. They use data from 1994 to 2003 on one index and nine commodity futures. The new aspect of their research is to study the influence of including leverage into portfolio optimization. Their first finding is that using or not using leverage does not affect the performance of the actual strategy. However, if restriction on investment behavior is forced the performance of levered and collateralized strategies differ. The performances of strategies that use or not use leverage are similar and using leverage would not cause a margin call number so high that disrupts the strategy. They also find that rebalancing the portfolio more frequently does not always improve the performance of the strategy.

3. DATA

The dataset from *datastream international,* which is used to conduct this research, consists of daily returns and roll-returns on 37 commodity futures from January 1, 1979 to October 31, 2011. The list of 37 commodities consist of 10 metal commodity futures (aluminum, copper, gold, lead, nickel, palladium, platinum, silver, tin, zinc), 4 livestock commodity futures (feeder cattle, frozen pork bellies, lean hogs, live cattle), 6 energy commodity futures (Brent crude oil, crude oil, gas oil, heating oil, natural gas, unleaded gasoline), 13 agricultural commodity futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, wheat Kansas City, wheat CBOT, white wheat), the futures on milk and lumber and two non overlapping diammonium phosphate contracts. To avoid survivorship bias, contracts that started trading after January 1979 or were delisted before January 2007 are included. The total sample size ranges from a low of 22 contracts at the beginning of the sample period to a peak of 35 contracts from July 1997 onwards.

If P_i^j is the closing price of commodity *j* at day *i*, the return of the commodity *j* at day *i* is defined as follows:

$$r_i^j = \ln\left(\frac{P_i^j}{P_{i-1}^j}\right) \quad (1)$$

Also, if NF_i^j is the nearest future closing price of commodity j at time i and SF_i^j is the second nearest future contract's closing price on the commodity *j* and time *i*, the roll return is defined as follows:

$$roll_i^j = \ln\left(\frac{NF_i^j}{SF_i^j}\right) \quad (2)$$

The factor identifying the roll return is term structure of commodity futures prices. There are three different scenarios possible. First, when futures prices and spot prices are the same, or in other words we have an absolutely flat term structure of futures prices, we should have the same excess and spot return. Second, when spot prices are above the future prices, then excess returns should be above spot returns. Last, when spot prices are lower than future prices, then excess returns should be lower than spot returns. To further illustrate roll returns, an example from Erb and Harvey (2005) based on the price of crude oil futures is given. The crude oil future price drops at the beginning of June 2004, as the maturity of the future contract rises. July 2004 future contract was priced at \$40.95 per barrel and \$36.65 per barrel for June 2005 contact, which gives the definition of market backwardation. Assuming the spot price to be equal to the nearest future contract price, going long the July 2005 oil contract would yield a roll return of 14% (*ln(\$40.95/\$36.65) = 13.8%*). This definition is directly extracted from Erb and Harvey (2005) and would be a measure for the degree of backwardation and contago of commodities. To minimize the possible liquidity issue, the strategy would trade the nearest future contract and hold it until the end of the month prior to its maturity and roll to the second-nearest future contract (Fuertes, Miffre, and Rallis, 2010).

The strategy assumes the investor holds a fully collateralized long and a fully collateralized short sub-portfolio. As the same collateral is used for both long and short sub-portfolios, the portfolio of long and short positions are therefore, by definition, 50% collateralized. In other words, the investor is using a leverage ratio of 2 in this strategy.

The return of the final portfolio at day i is simply calculated as the return of the long portfolio minus the return of the short portfolio (Gorton and Rouwenhorst, 2006) as follows:

$$R_i = Long\ Portfolio's\ R_i - Short\ Portfolio's\ R_i \quad (3)$$

The total return of the strategy from day *1* to day *n* is simply the sum of all returns (the log returns are linear and can be added together):

$$R_{strategy} = \sum_{i=1}^{n}(R_i) \quad (4)$$

The amount held as collateral is used to cover any possible margin call and is also assumed to be earning interest at the risk free rate. The performance is measured and reported as the excess return, which will eliminate the need to use a proxy for the risk free rate. However, any possible margin call payment will, in practice, be excluded from the collateral and therefore not earn interest anymore. This research underestimates the performance of the strategy by the amount of interest earned on the collateral minus the amount used for any margin call payments. If the strategy loses more than 50% in total, there would be a need for additional money to pay the margin calls.

4. Double-sort Strategy

4.1 Methodology

Implementing trading strategies on equity markets that select their portfolio based on momentum signals have been studied extensively and shown to generate abnormal return (Jegadeesh and Titman, 1993, 2001). It has also been proven that such strategies could be used to generate high returns on commodity futures markets Miffre and Rallis (2007).

Although it may seem that the two selection criteria, selection based on momentum and selection based on roll-return, are somehow overlapping and would both result in similar short-list of commodities as outcome, Fuertes, Miffre, and Rallis (2010) have shown the methods have rather low correlation (correlation between 10.92% and 56.96%). This encourages implementing and studying this double-sort strategy for various reasons such as generating returns and risk diversification.

Double-sort strategy based on roll return and momentum signals on commodity futures market has been implemented in Fuertes, Miffre, and Rallis (2010). This research implements a strategy identical to that of the mentioned paper. The portfolio consists of long and short positions. A short-list of commodities is used to form a portfolio at any given time. This short-list is derived as a result of sorting all the available commodities on two different levels. On the first level, the commodities are sorted based on their average momentum return during the ranking period (R). Using the results, the commodities are divided into three groups. The first group, *winner*, contains the 8 commodities with highest average return during the ranking period. The second group, *loser,* contains the 8 commodities with the lowest average return during the ranking period. The third group, which are commodities with average return lower than the winner group but higher than the loser groups are ignored. Next, the second sort based on the roll-returns are applied which further narrows down the outcome of the first sort. We start with sorting the winner group based on the commodities average roll-returns during the ranking period (Basu and Miffre, 2012). The 4 commodities with the highest roll-return are then labeled as *winner-high* and are used to form the long positions in the final portfolio. Similarly, the 4 commodities with the lowest roll-return, *loser-low,* are selected from the loser group and form the short positions of the final portfolio. The rest of the commodities from the first sort are ignored and don't play a role in the portfolio formation. Thus, the final portfolio consists of 4 long positions, winner-high, and 4 short positions, loser-low. This portfolio is then held for the holding period (H). No rebalancing would occur on this portfolio during the holding period.

At any day, if for any reason no return is available for a certain commodity that is included in the portfolio at that time, the weight of that specific commodity is distributed evenly among other commodities available in the portfolio and the return of the portfolio is calculated accordingly.

The order of the sort, i.e. first sort based on momentum or first sort based on roll-returns, would not change the results meaningfully (Fuertes, Miffre, and Rallis, 2010) and therefore this research has focused on the strategy which sorts firstly based on momentum and secondly on roll-returns.

Fuertes, Miffre, and Rallis (2010) have tested different ranking and holding periods and concluded that choosing ranking period and holding period equal to one month would maximize the performance. We, therefore avoid testing this theory again and use holding period and ranking periods of 1 month to give the best results.

The long and short sub-portfolios are independently equally weighted at the formation date. The strategy, to avoid unnecessary rebalancing costs, allows weights to evolve based on the performance of each commodity involved in the portfolio formation. To do so, after the return of the portfolio is calculated at each day, the new position weights are calculated based on the return of each of the commodities that are available in the portfolio and their contribution to the final portfolio's return for that day. The position weights are then updated accordingly. Consequently, commodities that have lost value during the trading day would be less weighted in the tomorrow's portfolio and commodities that have gained value during the trading day would weight more in tomorrow's portfolio. At the end of each month and after the commodities are resorted and the new portfolio is formed, the portfolio would once again be equally weighted.

The strategy is tested in two different stages. For the first stage, the complete dataset, from January 1, 1979 to October 31, 2011, is used. This would allow examining the strategy in full and studying the performance of the double-sort strategy on commodity futures throughout a period of more than thirty years. It would give a dependable conclusion on whether such strategy is profitable in general and in long-term. This strategy has already been tested with data going up to 2007 (Fuertes, Miffre, and Rallis, 2010).

The second stage test is one of main purposes of this study; to check the performance of the strategy on different market conditions. For this stage, the data is divided into two different categories: pre-crisis and during-crisis. Data from January 1, 1979 to January 31, 2007 is used to calculate the strategy's performance before the recent financial crisis starts. For the second category, the data from February 1, 2007 to October 31, 2011 is used which would allow the comparison of the strategy's performance before and during the recent financial crisis. It is worth noting that, the data used in the second stage includes the sub-prime crisis of 2008 and the more recent and ongoing liquidity crisis.

4.2 Performance of full sample data

Table 1 illustrates the summary statistics when data from January 1,1979 to October 31, 2011 is used to preform the double sort strategy. The table shows the performance of the long, short, and combined portfolios separately. The strategy yields a positive return of

20.22% per annum[6] throughout the dates February 1, 1979 and October 31, 2011. Note that the January 1979 data is used for ranking the commodities and forming the initial portfolio and have not been included in the results. This return is both economically and, with a t-value of 4.58, statistically significant at 95% confidence interval. During this time the long and short sub-portfolio have generated a return of 12.28% and 7.94%[7] respectively. The strategy has an annual volatility of 24.91%. The long sub-portfolio has a slightly higher annual volatility, 20.54%, compared to the short sub-portfolio with 19.05%. Another meaningful statistic to consider is downside volatility. Downside volatility is calculated as the volatility of negative returns. The strategy shows 17.13% as for the downside volatility with 14.52% for the long and 13.15% for the short sub-portfolios. The "reward to risk" and "sortino" ratios of the portfolio are 0.81 and 1.18 respectively.

	FULL SAMPLE		
	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.22%**	**12.28%**	**-7.94%**
t-statistics	4.58		
Mean	0.08%	0.05%	-0.03%
Median	0.04%	0.05%	0.00%
Standard Deviation(annual)	**24.91%**	**20.54%**	**19.05%**
Sample Variance	0.02%	0.02%	0.01%
Kurtosis	5.3904	7.865	7.356
Skewness	-0.1481	-0.3445	0.0317
Range	0.2007	0.2067	0.1764
Minimum	-0.1203	-0.1274	-0.0887
Maximum	0.0804	0.0793	0.0876
Sum	663.66%	401.79%	-261.88%
DownSide Vol	**17.13%**	**14.52%**	**13.15%**
Reward/Risk	**0.81**	**0.60**	**0.42**
Sortino	**1.18**	**0.85**	**0.60**
30 day VaR(99%)	**20.27%**	**18.49%**	**13.25%**
%of positive months	51.27%		
Count	8543		

Table 1 - Performance of the double-sort strategy using data from 1979 to 2011

[6] Return is annualized on actual/actual basis.
[7] Since the short positions would generate positive returns when their mathematical return is negative, the final return is reported in this report rather than the mathematical return.

In the double sort strategy, the portfolio consists of long and short positions at the same time. Out of the 20.22% total return per annum of the strategy, the long positions and short positions return 12.28% (60.7% of total return) and 7.94% (39.3% of total return) annually. Thus, even with the same number of long and short positions in the final portfolio at all times the strategy generates the higher percentage of its performance out of available long positions in the portfolio rather than short positions. Moreover, the annual volatility of the long and short sub-portfolios is 20.54% and 19.05% respectively, which are both below the final portfolio's annual volatility of 24.91%. However, the reward to risk and sortino ratios show that including long and short positions in the portfolio at the same time improves the risk-adjusted investment over any of the sub-portfolios individually. The reward to risk ratio of long, short and combined portfolio are 0.6, 0.42, and 0.81 respectively; similarly, 0.85, 0.6, 1.18 as for the sortino ratios of the long, short, and combined portfolio.

Figure 3 shows the $1 evolution graph and compares it to S&P GSCI[8] (Goldman Sachs Commodity Index) and S&P500 equity index as two benchmarks. $1 investment in the double sort strategy on February 1, 1979 would have evolved into $7.63 by the end of October 2011.

[8] Note that the S&P GSCI is not available until January 8, 1991. For the sake of comparison, the initial dollar value invested in S&P GSCI is set equal to the return of the double sort strategy at the beginning of the index availability.

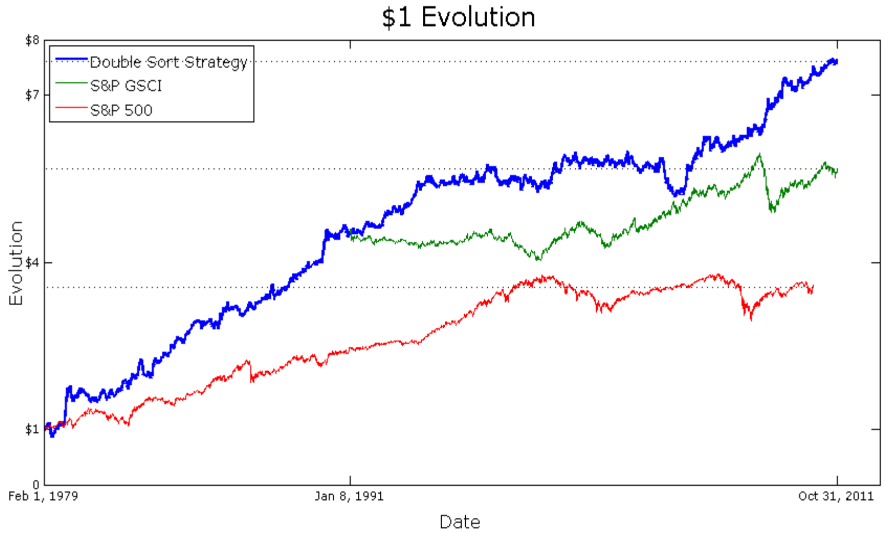

Figure 3 - The evolution of $1 invested in double-sort strategy compared to benchmarks

4.3 Performance of the double sort strategy, pre and during the crisis.

Is the high performance of double sort strategy due to the fact that commodity prices have been in an uptrend for a long period of time? Does this performance fade away within the financial crisis and, consequently, the drop of commodity prices? Although this may be probable for long-only investments, this strategy is using both long and short positions to form a portfolio. In this section, in order to shed light on the performance of such trading strategies, we would examine the performance of the double-sort strategy during different market cycles.

As explained in the methodology, the data has been separated into two different categories; first, data from January 1, 1979 up to January 31, 2007, which hereafter is called *pre-crisis* era and second, data from February 1, 2007 to October 31, 2011, which is referred to as *crisis* era. The result of this comparison will show how a specific long-short strategy, double-sort strategy on commodity futures, would preform both in an uptrend market condition and in one of the most serious economic downtrends in recent history.

The long-short strategy, by definition, should be able to preform well in both uptrends and downtrends with long positions making profit as the prices rise and the short positions as the prices fall. Table 2 and Figure 4 summarize the results for the pre and during the crisis periods. Not surprisingly, the double-sort strategy yields a positive annual return of 17.12% in the pre-crisis era. The same strategy interestingly generates a considerable positive return of 34.50% per annum during the crisis. This return is both economically and statistically significant at 95% confidence level. The volatility of the strategy rises from 24.36% for pre-crisis to 27.92% during the crisis. However, the reward to risk and sortino ratios show that the higher return more than compensates for the higher risk associated with the crisis. Reward to risk and sortino ratios are 0.7 and 1.02 for the pre-crisis and 1.24 and 1.83 for the during-crisis respectively. Downside volatility has also risen from 16.85% to 18.88% as we move from pre-crisis to the crisis period.

	BEFORE CRISIS			*CRISIS*		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**17.12%**	**9.63%**	**-7.49%**	**34.50%**	**23.43%**	**-11.08%**
t-statistics	3.69			2.60		
Mean	0.07%	0.04%	0.03%	0.13%	0.09%	-0.04%
Median	0.03%	0.03%	0.00%	0.11%	0.12%	0.00%
Standard Deviation(annual)	**24.36%**	**19.83%**	**17.70%**	**27.92%**	**24.50%**	**25.68%**
Sample Variance	0.02%	0.02%	0.01%	0.03%	0.02%	0.03%
Kurtosis	5.6709	8.9392	6.2515	4.2148	4.3624	7.11
Skewness	-0.1705	-0.3676	0.1018	-0.1024	-0.2809	-0.0867
Range	0.2007	0.2067	0.1629	0.1418	0.1366	0.1725
Minimum	-0.1203	-0.1274	-0.0752	-0.0738	-0.0659	-0.0877
Maximum	0.0804	0.0793	0.0876	0.0680	0.0707	0.0838
Sum	479.39%	269.60%	-209.78%	163.73%	111.16%	-52.56%
DownSide Vol	**16.85%**	**14.07%**	**12.28%**	**18.88%**	**17.18%**	**17.48%**
Reward/Risk	**0.70**	**0.49**	**0.42**	**1.24**	**0.96**	**0.43**
Sortino	**1.02**	**0.68**	**0.61**	**1.83**	**1.36**	**0.63**
30 day VaR(99%)	**20.79%**	**17.85%**	**12.72%**	**14.08%**	**34.76%**	**19.80%**
%of positive months	50.99%			52.14%		
Count	7305			1238		

Table 2 - Performance of the double-sort strategy pre and during the crisis

During the same time, the S&P GSCI shows a 110% increase in return from 4.34% before-crisis to 9.10% during-crisis while the double sort strategy shows a slightly less percentage rise in return with a 102% increase. However, the reward to risk and sortino ratios of the double sort strategy show 77% and 79% improvement compared to 41% and 39% of the benchmark. This means that during the crisis the double-sort strategy increases its risk-adjusted performance more than S&P GSCI does. The double-sort strategy's increase in the risk measures is more than compensated by the increase in the return. The above results are due to the fact that long-short strategies generate higher returns in volatile market conditions. The annual volatility of the S&P GSCI has risen from 19.34% before the crisis to 29.1% during the crisis.

A correlation study would help explain the results further. The correlation of double sort strategy and S&P GSCI as a commodity index is 13.23% before the crisis. Interestingly this correlation drops to -9.75% during the crisis, i.e. from February 1, 2007 to October 31, 2011. According to this result, it is safe to conclude that although both the returns of the double sort strategy and S&P GSCI have risen more than 100% as the crisis appears, the higher double sort strategy is not correlated with the climbing of the benchmark.

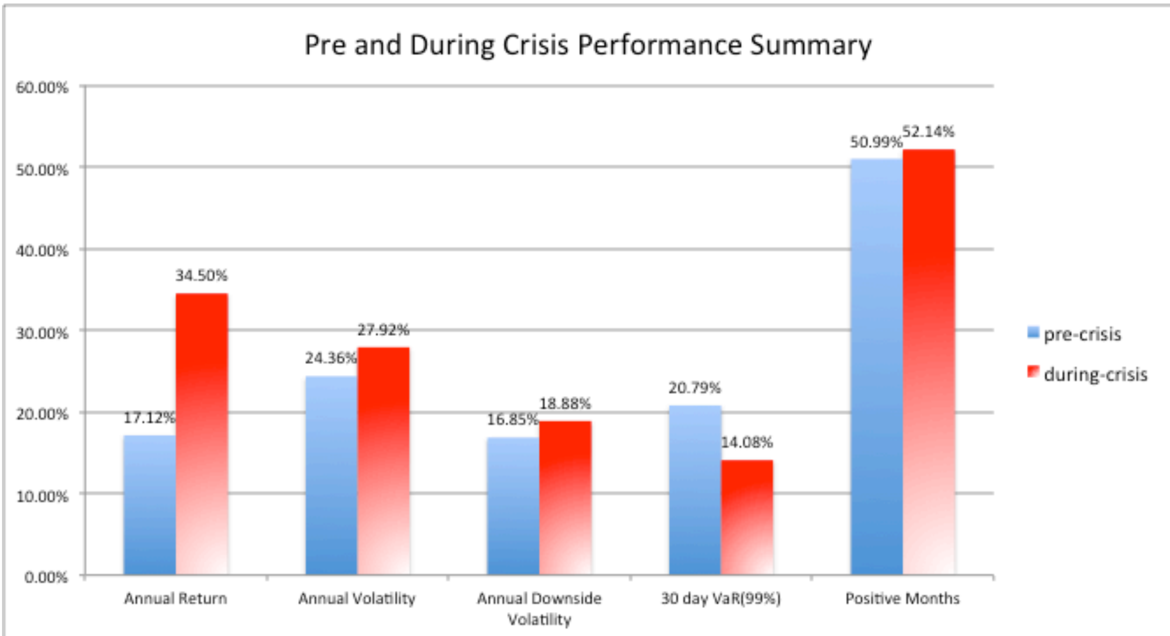

Figure 4 - Performance of the double-sort strategy pre and during the crisis

It would also be interesting to study the performance of the double sort strategy based on the long and short positions available in the portfolio individually. As for the pre-crisis era, with a return of 9.63% per annum, the long positions are responsible for 56.25% of the portfolio's total performance while at the same time the short positions have yielded 7.49% per annum. During the crisis, the long positions are generating 67.9% of the strategy's total return. Despite the initial feeling that promotes the higher role for the short positions in generating the total performance, the short positions have contributed to 32.1% of the total performance, which has fallen from 43.75% in the pre-crisis period.

Also comparing the double-sort strategy to S&P 500 equity index as a second benchmark would be useful. As shown in figure 5, the S&P 500 returns are 7.83% and -2.83% pre and during the crisis. This is significantly below the return of the double-sort strategy. Moreover, the Annual volatility and downside volatility of the benchmark is comparable to those of the double-sort strategy, leaving the benchmark's risk-adjusted performance far below that of the double-sort strategy. The pre-crisis risk to reward ratio of the benchmark is 0.59 compared to 0.7 for the double-sort strategy. Similarly, the sortino ratio of the benchmark is 0.82 is below that of the double-sort strategy with 1.02. The difference in the performance between the strategy and the benchmark becomes bigger as the crisis emerges. In the crisis, the reward to risk ratio and sortino ratio of the benchmark are -0.11 and -0.14 while for the double-sort strategy the ratios are 1.24 and 1.83 respectively.

As results show, the double sort strategy is a profitable strategy not only during the periods when the market is preforming well but also in periods of crisis. The strategy also outperforms the S&P GSCI and S&P 500 in both return and risk-adjusted return considerably. Figure 5 gives a comparison of double-sort strategy with S&P GSCI and S&P 500 as two benchmarks. The strategy's performance improves notably in the crisis era and therefore, it's safe to conclude that the strategy is profitable during both upward and downward market conditions. Importantly, during the crisis, when other asset classes such as equity tend to preform badly, the long-short double-sort strategy on commodities futures can generate high returns. Therefore, it's valuable to include such strategy in ones investment portfolio.

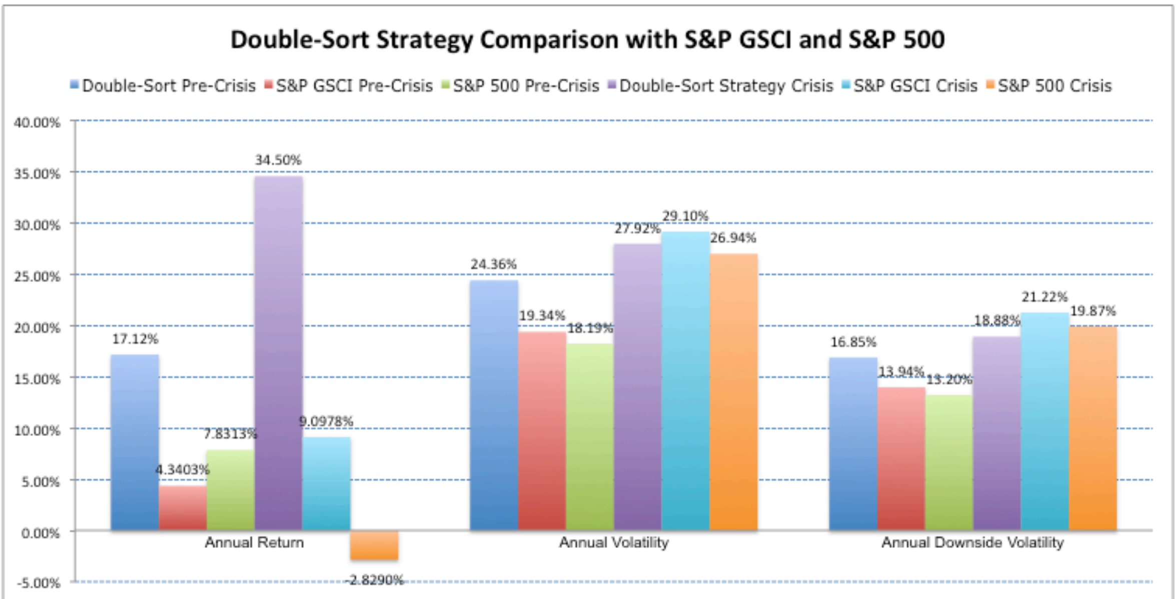

Figure 5 - Performance of the double-sort strategy compared to S&P GSCI and S&P 500 pre and during the crisis

5. Stop-loss Methods

5.1 Double-sort strategy with stop-loss

As discussed the double-sort strategy presents a profitable trading strategy on commodities futures market, both on a increasing and decreasing market conditions. The risk-adjusted performance is also high enough to motivate investors to include such strategy in their final portfolio both for generating returns and diversification. However, the risk numbers in isolation are higher than those of benchmarks such as S&P GSCI and S&P 500. If the strategy could be modified in a way to reduce risk numbers, it would be even more interesting and also safer to adapt such strategy. One way to do so is to include a stop-loss in the strategy with the hope of reducing the risk measures. In this study we attach various types of stop-loss triggers and study the performance of the adapted strategy compared to that of the double-sort strategy without a stop-loss, which we call the classic double-sort strategy. The goal is to keep the return at nearly the same level whilst reducing the risk measures such as volatility, downside volatility and consequently increasing the reward to risk and sortino ratios.

5.2 Methodology

Stop-loss is defined as a trigger by which the commodity future positions in the final portfolio are closed when the portfolio is losing value with the hope of cutting the future losses. As stated in the last section, the double-sort strategy builds a portfolio by buying the high-winner commodity future contracts and selling the low-loser ones and holding such combination of future contract positions for the duration of the holding period. In the holding period the positions would evolve in weight based on their performance but no position altering would occur. The stop-loss simply monitors the portfolio's performance both on a combined and individual level during the holding period and closes positions, by going long the short positions and shorting the long positions, based on certain criteria to reduce the possible loss of the strategy. Therefore, by definition, the stop-loss would not affect the selection process of the commodities, i.e. the double-sort selection criteria, and only affects the commodities already selected to build the portfolio at the beginning of the holding period. Clearly, the criteria by which the stop-loss would close the losing positions is the vital part of the process. We have implemented and studied the stop-loss using four different triggering criteria which are described separately below.

5.2.1 Cumulative loss method

The simplest method in triggering the stop-loss is the cumulative loss method. In this method the stop-loss component monitors each of the long and short positions in the portfolio since the day of the portfolio formation, i.e. the beginning of the holding period. The stop-loss component, at each day, calculates the cumulative loss of all the individual positions that are available in the current portfolio starting from the current day and going back as far as the first day of the current holding period. The cumulative loss is defined as the negative of the sum of the returns for the long positions and sum of the returns for the short positions during the current holding period. If the cumulative loss of any specific position is higher than a pre-specified *threshold*, that position is stopped and excluded from the portfolio, starting the next day and for the remainder of the current holding period. Stopping the position is implemented by forcing the weight of the position to zero and distributing that weight evenly among other available positions in the portfolio. This process is repeated every day with the remaining positions in the portfolio. There is also no restriction forced on the minimum number of available positions in the portfolio. This means that based on the performance of the commodities during any holding period, it is possible that all the positions would be eventually stopped and thus, there would be no portfolio available until the next holding period.

Choosing the value for the threshold is also an important measure. A small threshold would stop the positions too often and possibly unnecessarily and would therefore decrease the profit of the strategy while a big threshold would decrease the number of stop occurrences and make the strategy similar to one without any stop-loss. Different values for the threshold has been tested during the implementation phase but two are reported in this report: 5% and 13%. Any value below 5% dramatically decreases the return of the strategy without improving the risk-adjusted performance. Similarly, with values above 13% the performance of the strategy is not meaningfully different from that of the double-sort strategy without a stop-loss and therefore ignored.

An extension to the mentioned stop-loss strategy is one in which the stopped positions are still monitored even after they are closed. The intention is to allow the possibility of reopening the stopped positions if they make back their loss before the end of the holding period. To do so, at each day a *cumulative gain* is calculated for the stopped positions during the period of the day they were stopped and the current day. The cumulative gain is defined as the sum of returns for the stopped long positions and the negative of sum of returns for the stopped short positions during the mentioned period above. If the cumulative gain is above the same threshold that was used to stop the positions, the positions would be reopened from the next day. To reopen a position, its weight would be set to the same weight it had on the day of its stop and that weight would be evenly deducted from the weight of other available positions in the portfolio at that time. From that point, the reopened position is regarded as a normal position and is subject to being stopped if its cumulative loss reaches the threshold again. The performance of the cumulative stop-loss method is discussed thoroughly in results section.

5.2.2 Exponentially weighted average stop-loss method

One possible drawback of the cumulative stop-loss method is that it gives the same weight to losses occurred on any day during the holding period. It would be reasonable to assume that if prices follow a momentum-like behavior, a stop-loss trigger that gives more weight to recent losses is preferable. In this case, the recent losses would have more influence on the stop-loss trigger than the data from the early days of the holding period. For example, when a sudden change in the trend of one of the positions occurs, the stop-loss would not wait until the whole past profits of the position is wiped out and a loss bigger than the threshold has accumulated before it stops the losing position.

To modify the stop-loss trigger to take into account the day weights, we have employed an exponential average model. In this method instead of a simple cumulative loss, exponential average loss is calculated using the formulas below:

$$l_k^j = \frac{(1-\lambda)\lambda^{k-1}}{\sum_{i=1}^{n} \lambda^{i-1}} \left(-r_k^j\right) \qquad (5)$$

$$L^j = \sum_{k=1}^{n} l_k^j \qquad (6)$$

Where l_k^j is the exponential loss of commodity j at day k, λ is the exponential factor, r_k^j is the return of commodity j on day k, L^j is the exponential average loss of commodity j during the period that starts at the first day of the holding period and ends on the current day *(n)*. We have used a exponential factor of 0.6 ($\lambda = 0.6$) for the calculation. This means that the model uses a 40% weight for the loss occurred on the current day in the calculation of the average. The weights exponentially decrease as the data move away from current day towards the beginning of the holding period.

In this method, we calculate the exponential average loss for each commodity in the long and short portfolios at any day. If this average loss is bigger than a certain threshold, the losing position would be closed until the end of the holding period and its weight would be evenly distributed among other available positions within its portfolio (depending on whether the losing position is a long or short position). This procedure repeats itself every day until the next holding period where the commodities are resorted and a new portfolio is formed. The results for exponentially weighted average with an exponential factor of 0.6 and a threshold of 5% are discussed in the results section.

5.2.3 Consecutive loss stop-loss method

Another way to look at the price trend is to emphasize the number of losing days instead of the amount of loss. The number of days a commodity future contract is making or losing money in a period could be an alternative signal for trend change. As for the stop-loss strategy, we expand on this idea and present a stop-loss method that triggers based on the consecutive number of losing days. In this method, as opposed to the previous two methods, the amount of loss is ignored. Instead, a *consecutive loss* measure is calculated at each day.

Consecutive loss is simply defined as the number of days that a long position has had negative returns or a short position has had positive returns. For the calculation, we start at the current day and go back until we reach the first day of the holding period or the loss pattern breaks, whichever occurs first. Next, the consecutive loss measure is compared to a pre-specified threshold. If the consecutive loss is bigger than the threshold, i.e. the position has lost more than "threshold number of days in a row", the position will be stopped from the next day and throughout the end of the current holding period. The closing is done by setting the weight of the losing position to zero and evenly distributing its weight among other available positions in its sub-portfolio, depending on it being a long or a short position. This procedure is repeated every day for the remainder of the holding period.

Different amounts for threshold has been tested, but we report the results when the threshold is set to 5 days as the optimum number in the results section.

5.2.4 Full-portfolio cumulative stop-loss method

In all the previous stop-loss methods, the positions are monitored in isolation and based on different criteria the stop-loss would close the losing position and eliminate it from the current positions in the portfolio. The rest of the positions, however, would be remained open and the portfolio continues to accumulate returns. The performance of any of the commodities in the portfolio would not affect the other commodities.

In this method, we would not monitor all the available positions in the portfolio separately. Rather, the performance of the portfolio as a whole is under supervision. We implement the stop-loss similar to the cumulative stop-loss but this time the monitoring occurs on a portfolio level instead of individual positions.

To do so, we redefine the *cumulative loss* measure. The cumulative loss is defined as the negative of return of the portfolio at each day. At the end of each day, the cumulative loss is compared to a pre-specified threshold. If the cumulative loss is bigger than the threshold, all the available positions in the portfolio, including long and short positions, are closed for the next day. Closing the portfolio is done by setting all the weights of the individual positions to zero. Once the portfolio is closed, it will neither gain nor lose any value from the next day until the next holding period starts. On the next holding period, the commodities are resorted and a new portfolio is formed using the double-sort strategy.

A similar extension to that of the cumulative stop-loss method is implemented as well. This extension allows the possibility of reopening the closed portfolio should the losses have been recovered. To do so, after the portfolio is closed the theoretical return of the portfolio is calculated, as it was still open. If at any day the calculated return is above the threshold that was used to close the portfolio, the portfolio would be reopened the next day. Reopening the portfolio is done by setting the weight of the participating commodities in the closed portfolio to the same amount they had on the closing day of the portfolio.

From that point, the portfolio is considered as a normal portfolio and is subject to reclosing should the loss increases above the threshold once again.

Different values for the threshold are examined and the results for the threshold of 5% are reported in the results section.

5.3 Performance of the stop-loss methods

In this section, we present the results of the doubt-sort strategy with the proposed stop-loss triggers and discuss these results compared to that of the classis double-sort strategy, i.e. double-sort strategy without stop-loss. At the end of this section, we can decide whether adding a stop-loss to the double-sort strategy affects the performance of the strategy and reduces the risk-measures.

5.3.1 Cumulative stop-loss method

Table 3 illustrates the performance of the cumulative stop-loss method with both 13% and 5% thresholds and compares them to the classic double-sort strategy without stop-loss. The cumulative stop-loss only slightly improves the performance of the strategy in 13% threshold whilst with 5% threshold the strategy performs worse than without stop-loss. Also, when preforming a paired-sample t-test on the strategy without a stop-loss and the strategy with cumulative stop-loss and 13% threshold, we can reject the null-hypothesis of the two samples being the same at 5% confidence level with a p-value of 3.62%. However, with a p-value of 64.75%, the results of the strategy without a stop-loss and a cumulative stop-loss of 5% are not statistically different.

	FULL SAMPLE, without stop-loss			*FULL SAMPLE, CUMULATIVE STOP-LOSS 13% threshold, without reopening*			*FULL SAMPLE, CUMULATIVE STOP-LOSS 5% threshold, without reopening*		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.22%**	**12.28%**	**-7.94%**	**20.97%**	**12.71%**	**-8.26%**	**15.65%**	**13.48%**	**-2.17%**
t-statistics	4.58			4.71			3.20		
Mean	0.08%	0.05%	-0.03%	0.0008	0.0005	-0.0003	0.0006	0.0005	-0.0008
Median	0.04%	0.05%	0.00%	0.0005	0.0004	0.0000	0.0005	0.0004	0.0000
Standard Deviation(annual)	**24.91%**	**20.54%**	**19.05%**	**25.07%**	**20.46%**	**19.11%**	**27.46%**	**21.25%**	**20.45%**
Sample Variance	0.02%	0.02%	0.01%	0.025%	0.017%	0.014%	0.030%	0.018%	0.017%
Kurtosis	5.3904	7.865	7.356	5.99	8.9519	8.7588	10.2863	13.4097	15.5185
Skewness	-0.1481	-0.3445	0.0317	-0.1695	-0.4265	0.0553	-0.3421	-0.1926	0.7450
Range	0.2007	0.2067	0.1764	0.2319	0.2254	0.2200	0.4003	0.3402	0.2888
Minimum	-0.1203	-0.1274	-0.0887	-0.1383	-0.1454	-0.0900	-0.2047	-0.1611	-0.0899
Maximum	0.0804	0.0793	0.0876	0.0936	0.0800	0.1300	0.1956	0.1792	0.1989
Sum	663.66%	401.79%	-261.88%	686.76%	416.25%	-270.51%	512.43%	441.51%	-70.92%
DownSide Vol	**17.13%**	**14.52%**	**13.15%**	**17.26%**	**14.47%**	**13.19%**	**19.41%**	**14.86%**	**14.78%**
Reward/Risk	**0.81**	**0.60**	**0.42**	**0.84**	**0.62**	**0.43**	**0.57**	**0.63**	**0.11**
Sortino	**1.18**	**0.85**	**0.60**	**1.22**	**0.88**	**0.63**	**0.81**	**0.91**	**0.15**
30 day VaR(99%)	**20.27%**	**18.49%**	**13.25%**	**20.88%**	**21.47%**	**14.24%**	**22.47%**	**17.20%**	**16.93%**
%of positive months	51.27%			51.47%			51.41%		
Count	8543			8543			8543		

Table 3 - Performance of the double-sort strategy without stop-loss and with cumulative stop-loss, 13% and 5% thresholds

The return of the strategy with 13% threshold, 20.97%, is very close to that of without stop-loss, 20.22%. However with a threshold of 5% the return drops to 15.65%. The annual volatility of the strategy with 13% threshold and 5% threshold are 25.07% and 27.56%, which are higher than 24.91% for the strategy without s stop-loss. The number of positive months for all three strategies is almost the same. On the risk-adjusted performance level, the 5% threshold strategy is performing worse than the three with a reward to risk ratio of 0.57 and sortino ratio of 0.81. These ratios for the 5% threshold strategy is slightly better than those of the classic strategy with 0.84 (reward to risk) and 1.22 (sortino) for the 13% threshold and 0.81 and 1.18 for the classic strategy. Also inline with the results above is the VaR measure. The 99% 30 day VaR for the classic, 13% and 5% thresholds are 20.27%, 20.88%, and 22.47% respectively. Figure 6 below shows a graphical comparison of the 3 strategies.

With the presented numbers, we can see that the cumulative stop-loss is not improving the performance of the double-sort strategy as expected. Although the results of 13% threshold are marginally better than that of the classic double-sort strategy, we have to keep in mind that the stop-loss strategy will also increase the transaction costs as more trades occur as the result of stopping positions while in the classic double-sort strategy the trades occur only at the formation of the portfolio.

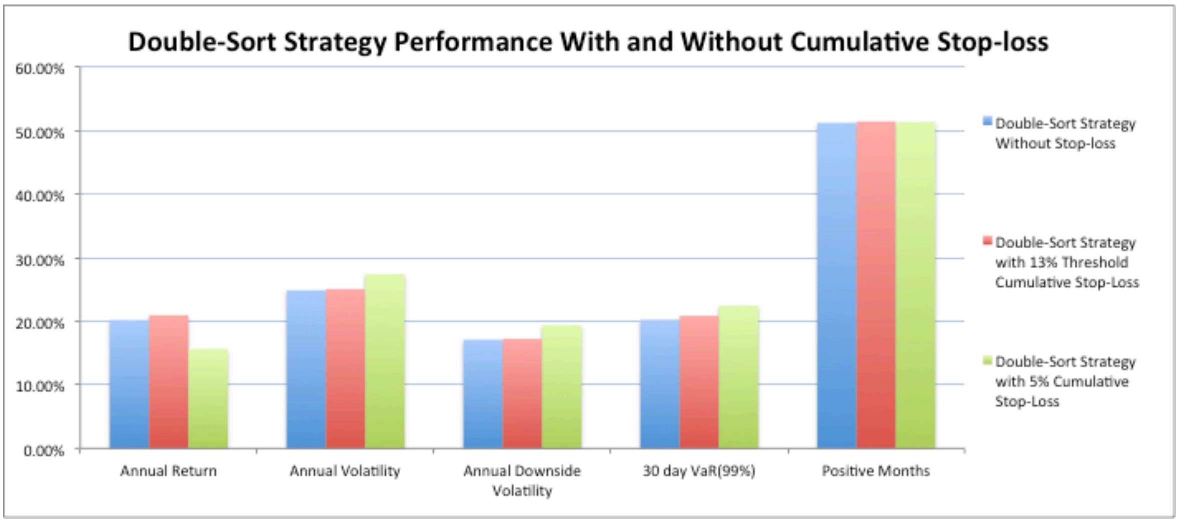

Figure 6 - Double-sort trading strategy performance with and without cumulative stop-loss

The performance of the double-sort trading strategy with reopening is not statistically different from that of without reopening; a paired-sample t-test shows a p-value of 19.06%. The summary of the comparison between the two is shown in table 4 below. The strategy with reopening shows indistinguishable risk-adjusted performance when compared to the stop-loss without reopening.

Thus it is safe to conclude, neither of the two forms of the cumulative stop-loss method, i.e. with and without reopening, are improving the performance of the strategy meaningfully. As stated above, if including the transaction costs in the calculations it is highly probable that the stop-loss even reduces the performance of the double-sort strategy because of the extra costs accumulated as a result of the additional contract closing and reopening. In the next section we study the performance of the exponentially weighted average stop-loss method as an alternative method to the cumulative stop-loss method.

	FULL SAMPLE, CUMULATIVE STOP-LOSS 13% threshold, without reopening			FULL SAMPLE, CUMULATIVE STOP-LOSS 13% threshold, with reopening		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.97%**	**12.71%**	**-8.26%**	**20.51%**	**12.25%**	**-8.26%**
t-statistics	4.71			4.61		
Mean	0.0008	0.0005	-0.0003	0.0008	0.0005	-0.0003
Median	0.0005	0.0004	0.0000	0.0005	0.0004	0.0000
Standard Deviation(annual)	**25.07%**	**20.46%**	**19.11%**	**25.01%**	**20.52%**	**19.11%**
Sample Variance	0.025%	0.017%	0.014%	0.025%	0.017%	0.014%
Kurtosis	5.99	8.9519	8.7588	5.8926	9.062	8.7578
Skewness	-0.1695	-0.4265	0.0553	-0.1922	-0.4527	0.0553
Range	0.2319	0.2254	0.2200	0.2315	0.2254	0.2200
Minimum	-0.1383	-0.1454	-0.0900	-0.1383	-0.1454	-0.0900
Maximum	0.0936	0.0800	0.1300	0.0931	0.0800	0.1300
Sum	686.76%	416.25%	-270.51%	671.70%	401.19%	-270.51%
DownSide Vol	**17.26%**	**14.47%**	**13.19%**	**17.26%**	**14.55%**	**13.19%**
Reward/Risk	**0.84**	**0.62**	**0.43**	**0.82**	**0.60**	**0.43**
Sortino	**1.22**	**0.88**	**0.63**	**1.19**	**0.84**	**0.63**
30 day VaR(99%)	**20.88%**	**21.47%**	**14.24%**	**22.47%**	**17.20%**	**16.93%**
%of positive months	51.47%			51.42%		
Count	8543			8543		

Table 4 - Performance comparison between 13% threshold cumulative stop-loss with and without reopening

5.3.2 Exponentially weighted average stop-loss method

As stated in the methodology, different values for the exponential factor and threshold have been used to test the strategy (see equations 5 and 6). The results for the best combination of values, i.e. exponential factor of 0.6 and threshold of 5% are reported in this section. The results of the exponentially weighted average stop-loss method are worse than the classic double-sort strategy without stop-loss. As the main result, the return of the method has dropped to 18.6% from the 20.22% of the classic method.

However, the return alone is not conclusive as long as the risk-measures also drop. The risk measures are the same as those of the classic strategy. The annual volatility is at 24.92% compared to 24.91% for the classic strategy. Downside volatility of the exponentially weighted average stop-loss method is 17.26% while this measure is 17.13% for the classic strategy. The 30-day VaR (99%) has slightly increased from 20.27% to 21.42% in the new method. Given the same risk measures and the lower return, the risk-adjusted performance of the new method is slightly below that of the classic strategy. The reward to risk and sortino ratios of the new method are 0.75 and 1.08 while the same ratios are 0.81 and 1.18 for the classic method respectively. Table 5 and figure 7 summarize the results and compare them to the classic double-sort strategy without stop-loss.

	FULL SAMPLE, WITHOUT STOP-LOSS			*FULL SAMPLE, EXPONENTIALLY WEIGHTED AVERAGE STOP-LOSS, 5% THRESHOLD, 0.6 EXPONENTIAL FACTOR*		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.22%**	**12.28%**	**-7.94%**	**18.60%**	**11.63%**	**-6.97%**
t-statistics	4.58			4.20		
Mean	0.08%	0.05%	-0.03%	0.0007	0.0004	-0.0003
Median	0.04%	0.05%	0.00%	0.0004	0.0004	0.0000
Standard Deviation(annual)	**24.91%**	**20.54%**	**19.05%**	**24.92%**	**20.30%**	**19.01%**
Sample Variance	0.02%	0.02%	0.01%	0.025%	0.016%	0.014%
Kurtosis	5.3904	7.865	7.356	5.7127	7.4951	7.3533
Skewness	-0.1481	-0.3445	0.0317	-0.1827	-0.2853	0.0499
Range	0.2007	0.2067	0.1764	0.2139	0.2067	0.1764
Minimum	-0.1203	-0.1274	-0.0887	-0.1203	-0.1274	-0.0877
Maximum	0.0804	0.0793	0.0876	0.0936	0.0793	0.0876
Sum	663.66%	401.79%	-261.88%	608.92%	380.83%	-228.10%
DownSide Vol	**17.13%**	**14.52%**	**13.15%**	**17.26%**	**14.30%**	**13.19%**
Reward/Risk	**0.81**	**0.60**	**0.42**	**0.75**	**0.57**	**0.37**
Sortino	**1.18**	**0.85**	**0.60**	**1.08**	**0.81**	**0.53**
30 day VaR(99%)	**20.27%**	**18.49%**	**13.25%**	**21.42%**	**20.28%**	**14.57%**
%of positive months	51.27%			51.16%		
Count	8543			8543		

Table 5 - Exponentially weighted average stop-loss and without stop-loss strategies performance comparison

Also, with a p-value of 14.72%, a paired-sample t-test statistically shows that the null hypothesis of the two samples not being different cannot be rejected.

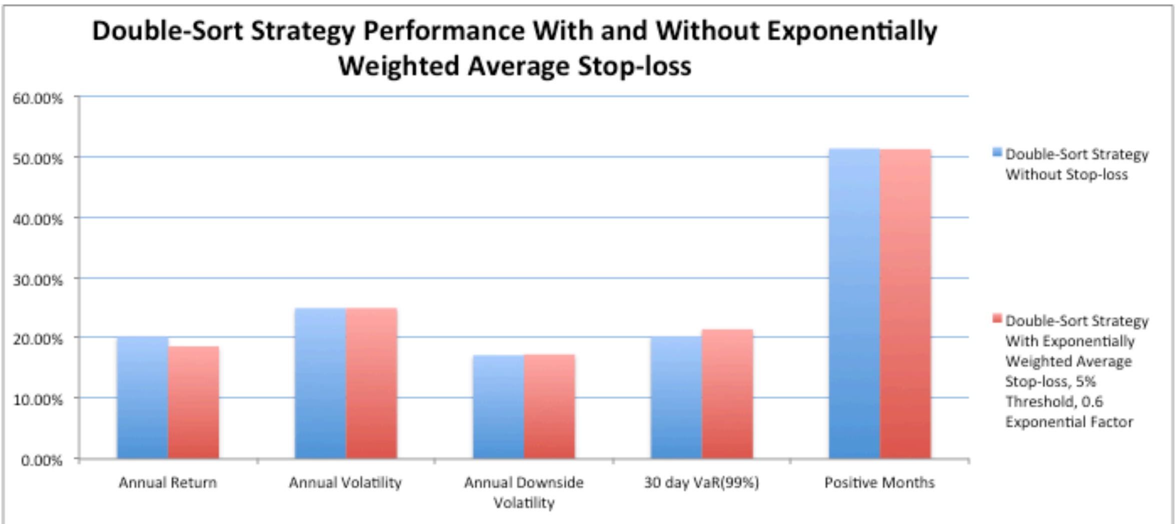

Figure 7 - Double-sort strategy performance with and without exponentially weighted average stop-loss

The performance of the exponentially weighted average stop-loss method is disappointing. The result of this method is even weaker than that of cumulative stop-loss. Due to extra transactions that may be necessary for stopping a position, this method also can have higher transaction costs compared to the strategy without stop-loss. If these cost are taken into account it will further reduce the performance of this method.

5.3.3 Consecutive stop-loss method

In this section we study the results of the consecutive stop-loss method. We have tested different values for the threshold in this method and the results of the threshold of 5 days, as the threshold that achieves the highest performance among other thresholds, is presented.

This method yields a return of 20.99% per annum as compared to the similar 20.22% for the classic double-sort strategy method. The annual volatility of the strategy rises from 24.91% for the classic double-sort strategy to 25.72% for the consecutive stop-loss method. Downside volatility for both methods is almost the same: 17.13% for the strategy without stop-loss and 17.70% for the recent method. The 30-day VaR (99%) of the recent method has dropped from 20.27% for the strategy without stop-loss to 18.88% for the consecutive stop-loss method.

	FULL SAMPLE, WITHOUT STOP-LOSS			FULL SAMPLE, CONSECUTIVE STOP-LOSS METHOD, 5 DAY THRESHOLD		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.22%**	**12.28%**	**-7.94%**	**20.9859%**	**12.5507%**	**-8.4352%**
t-statistics	4.58			4.59		
Mean	0.08%	0.05%	-0.03%	0.08%	0.05%	-0.03%
Median	0.04%	0.05%	0.00%	0.05%	0.04%	0.00%
Standard Deviation(annual)	**24.91%**	**20.54%**	**19.05%**	**25.72%**	**21.27%**	**19.43%**
Sample Variance	0.02%	0.02%	0.01%	0.03%	0.02%	0.01%
Kurtosis	5.3904	7.865	7.356	5.7311	9.4704	6.989
Skewness	-0.1481	-0.3445	0.0317	-0.1050	-0.3953	0.0164
Range	0.2007	0.2067	0.1764	0.2310	0.2360	0.1764
Minimum	-0.1203	-0.1274	-0.0887	-0.1203	-0.1274	-0.0877
Maximum	0.0804	0.0793	0.0876	0.1106	0.1087	0.0876
Sum	663.66%	401.79%	-261.88%	687.19%	410.98%	-276.21%
DownSide Vol	**17.13%**	**14.52%**	**13.15%**	**17.70%**	**15.09%**	**13.41%**
Reward/Risk	**0.81**	**0.60**	**0.42**	**0.82**	**0.59**	**0.43**
Sortino	**1.18**	**0.85**	**0.60**	**1.19**	**0.83**	**0.63**
30 day VaR(99%)	**20.27%**	**18.49%**	**13.25%**	**18.88%**	**18.54%**	**13.56%**
%of positive months	51.27%			51.46%		
Count	8543			8543		

Table 6 - Consecutive stop-loss and without stop-loss strategies performance comparison

On risk-adjusted level, the performance is indistinguishable for the two methods. The reward to risk ratio is 0.81 and 0.82 in favor of the consecutive stop-loss method and, similarly, the sortino ratio is 1.18 and 1.19 for the classic and consecutive stop-loss method respectively. Table 6 and figure 8 present a summary on the findings and compares them to the results of the classic double-sort strategy.

Paired sample t-test rejects the null hypothesis of the two samples being the same at 5% level with a p-value of 3.62%. However, the results are not economically different from each other. Despite the slightly higher return of the modified strategy, the stop-loss has failed to improve the risk-adjusted performance of the classic double-sort strategy meaningfully. Similar to previous findings, the performance of the stop-loss strategy would decrease, if the extra-transaction costs were taken into account.

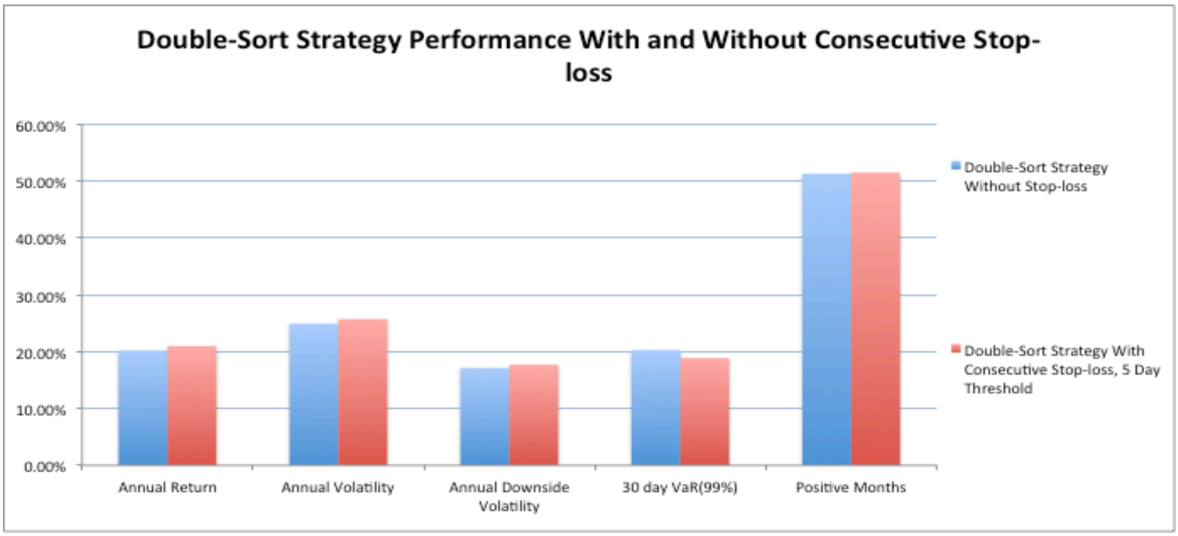

Figure 8 - Double-sort strategy's performance with and without consecutive stop-loss

5.3.4 Full-portfolio stop-loss method

The results of the full-portfolio stop-loss method with a threshold of 5% is presented in this section and compared to the classic double-sort strategy without stop-loss. The return of the method is consistent with that of the classic double-sort strategy; 20.22% for the classic strategy and 19.93% for the full-portfolio stop-loss method. The stop-loss has reduced the annual volatility of the strategy by more than 2% from 24.91% to 22.47%. The downside volatility has also slightly decreased from 17.13% for the classic strategy to 15.20% for the recent method. The 30-day VaR (99%) shows a bigger decrease in value. The 30-day VaR for the classis strategy and the full-portfolio stop-loss method are 20.27% and 13.76% respectively. Table 7 and figure 9 present the results and comparison of the full-portfolio stop-loss and classic double-sort strategy in detail.

	FULL SAMPLE, WITHOUT STOP-LOSS			*FULL SAMPLE, FULL PORTFOLIO STOP-LOSS, 5% THRESHOLD*		
	Final Portfolio	Long Portfolio	Short Portfolio	Final Portfolio	Long Portfolio	Short Portfolio
Annualized Return	**20.22%**	**12.28%**	**-7.94%**	**19.93%**	**14.11%**	**-5.82%**
t-statistics	4.58			4.99		
Mean	0.08%	0.05%	-0.03%	0.08%	0.05%	0.02%
Median	0.04%	0.05%	0.00%	0.00%	0.00%	0.00%
Standard Deviation(annual)	**24.91%**	**20.54%**	**19.05%**	**22.47%**	**18.64%**	**17.04%**
Sample Variance	0.02%	0.02%	0.01%	0.02%	0.01%	0.01%
Kurtosis	5.3904	7.865	7.356	5.5103	7.654	7.8549
Skewness	-0.1481	-0.3445	0.0317	-0.0090	-0.1618	-0.0301
Range	0.2007	0.2067	0.1764	0.1534	0.1643	0.1590
Minimum	-0.1203	-0.1274	-0.0887	-0.0081	-0.0895	-0.0752
Maximum	0.0804	0.0793	0.0876	0.0729	0.0748	0.0838
Sum	663.66%	401.79%	-261.88%	652.70%	462.01%	-190.70%
DownSide Vol	**17.13%**	**14.52%**	**13.15%**	**15.20%**	**12.90%**	**11.72%**
Reward/Risk	**0.81**	**0.60**	**0.42**	**0.89**	**0.76**	**0.34**
Sortino	**1.18**	**0.85**	**0.60**	**1.31**	**1.09**	**0.50**
30 day VaR(99%)	**20.27%**	**18.49%**	**13.25%**	**13.76%**	**14.97%**	**11.04%**
%of positive months	51.27%			43.17%		
Count	8543			8543		

Table 7 - Full-portfolio stop-loss and without stop-loss strategies performance comparison

The risk-adjusted performance of the recent stop-loss method, however with a slight improvement, does not show an economically meaningful increase over the classic double-sort strategy performance. The reward to risk ratio and sortino ratio for the full-portfolio stop-loss method are 0.89 and 1.31 compared to 0.81 and 1.18 for the classic strategy respectively. A paired sample t-test does not statistically reject the hypothesis of the two samples being indifferent at 5% with a p-value of 7.9%.

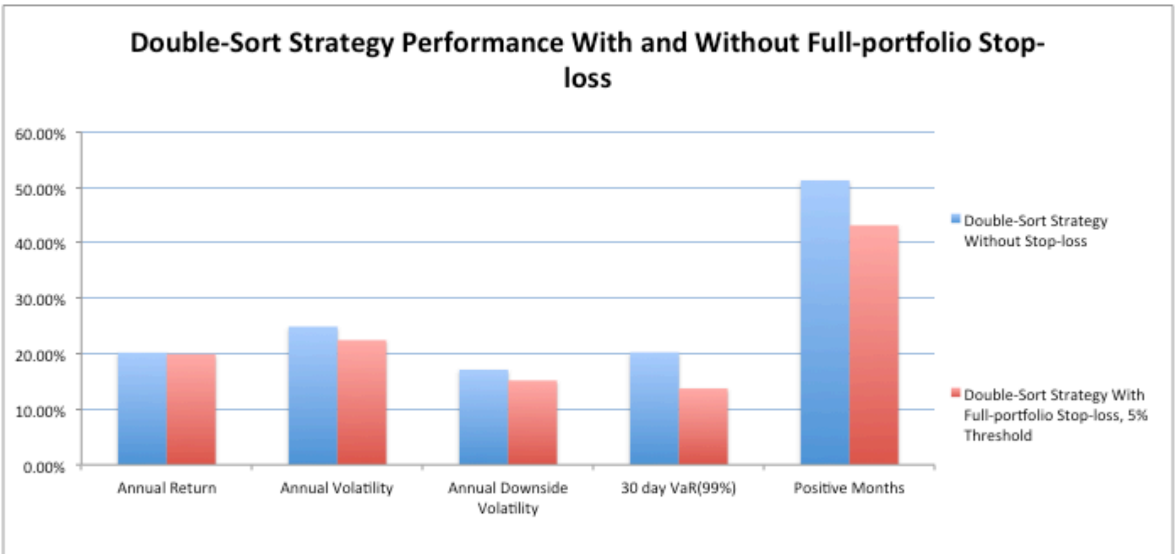

Figure 9 - Double-sort strategy's performance with and without full-portfolio stop-loss

The method is also tested when reopening the position is allowed with a threshold of 5%. The performance of such extension on the method was the same as the case for the cumulative stop-loss method; the performance is worse in all levels, i.e. return, risk measures, and risk-adjusted performance, when the reopening is allowed. Therefore, the detail of the results is not provided in this study.

The performance of the full-portfolio stop-loss is an improvement over the previous stop-loss methods and a slight improvement over the classic double-sort strategy. The return is higher and the risk measures are lower, thus the risk-adjusted performance of the strategy is higher than the classic double-sort strategy, which was the goal of implementing the stop-loss methods. However, the results are far below expectations and the improvement is only marginal. Also, this study does not take into account the transaction costs and therefore their exact influence on the performance is unknown.

6. Summary and Conclusion

For reasons such as equity-like returns, risk diversification, and inflation hedge, commodities have become a popular asset class for investment. There have been many studies exploring this opportunity and presenting ideas on profitable trading strategies on commodities.

Double-sort trading strategy was introduced by Fuertes, Miffre, and Rallis (2010). This active strategy, which is implemented on commodities futures market, sorts the commodities based on their past momentum and term-structure performance and forms a long-short portfolio of commodity futures. The portfolio is then held for a specific amount of time, i.e. the holding period. The strategy has shown to generate abnormal returns over the relatively long timeframe on which it was tested (from 1979 to 2007).

In this study, we, first, re-implemented the strategy and tested its performance on data from 1979 to 2011. We have come to the same conclusion as Fuertes, Miffre, and Rallis (2010) on the profitability of the strategy. The strategy has been tested for one month ranking period and one month holding period and yields 20.22% per annum from January 1979 to October 2010. The strategy's annual volatility, downside volatility and 30-day VaR (99%) are 24.91%, 17.13%, and 20.27% respectively. With a reward to risk ratio of 0.81 and sortino ratio of 1.18, the strategy proves profitable compared to two benchmarks, i.e. S&P GSCI with 0.24 and 0.34 for reward to risk and sortino ratios and S&P 500 with 0.43 and 0.59 for the same ratios respectively.

Next, we have tested to confirm the profitability of this strategy on different market conditions. For this purpose, we divided the data to two non-overlapping groups that represent two non-similar market conditions: pre and during the crisis. The pre-crisis era contains data from January 1979 to January 2007 and the crisis era from February 2007 to October 2011. Our findings confirm that the strategy is profitable during both eras.

Interestingly the strategy performs better during market fluctuations. The strategy returns 17.12% per annum before the crisis and 34.50% per annum during the crisis. Not surprisingly the risk measures also increase during the crisis. The strategy's annual volatility, downside volatility, and 30-day VaR (99%) are 24.36%, 16.85%, and 20.79% before the crisis whilst the same measures are 27.92%, 18.88%, and 14.08% during the crisis. The higher risk measures are, however, more than compensated by the higher return which results in a reward to risk and sortino ratio of 1.24 and 1.83 during the crisis compared to 0.70 and 1.02 before crisis.

The fact that the strategy's performance is boosted during the crisis comes from two possible reasons. First, the strategy builds a long-short portfolio, in contrast to a long-only strategy such as the S&P GSCI. The long positions make profit when prices are rising and short positions when prices are falling. Second, the strategy is an active strategy. This means that the portfolio is reconstructed at the beginning of every holding period based on the performance of the commodities and the commodities included in the previous portfolio have no priority in the new selection. If a commodity is not among top winners or losers it will be excluded from the portfolio.

The drawback of the double-sort strategy is the relatively high risk measures. Although these measures are not discouraging when they are looked at in combination with the high return, reducing them would make the strategy even more desirable. For this purpose, we have constructed a number of stop-loss methods and added them to the strategy.

First, a cumulative stop-loss method is constructed. The method monitors each position in the portfolio and closes the position should the loss of the position reach above a threshold. Two thresholds of 5% and 13% were presented in the results. In summary, the cumulative stop-loss method fails to achieve the expected improvement on the classic double-sort strategy. The risk-adjusted performance of such strategy is the same as that of the classic strategy. The method is also modified to allow reopening the closed positions should they regain the cumulated loss. The result of this modification is also disappointing. The performance of the stop-loss method slightly drops when reopening is applied. In addition, the stop-loss method, in general, may have extra transaction costs. This is due to the possible higher number of transactions in a stop-loss method than in a method without stop-loss.

Second, we replace the cumulative stop-loss method with an exponentially weighted average stop-loss method. The exponentially weighted average assigns more weight to recent losses. The motivation behind this method is to take into account the time that the loss occurs and make the recent loses more influential on the stop-loss decision-making process. However, the results show that this method fails to achieve the goal. This method of stop-loss reduces the performance of the double-sort strategy more than the cumulative stop-loss method does. The risk-adjusted performance of this method is below that of the cumulative stop-loss and the classic double-sort strategy in every aspect.

Third, an alternative strategy of stop-loss is practiced. Instead of looking at the accumulated loss, the consecutive stop-loss method takes into account the consecutive number of days that a position is losing. When a threshold of 5 days is reached, the losing position is closed. The results of this method are marginally better than those of the two last methods. While the risk-adjusted performance of the consecutive stop-loss method is nearly the same as the classic strategy, the method reduces the 30-day VaR (99%) by more than 1%.

Last, we replace the position monitoring with portfolio monitoring. In other words, in the three previous stop-loss methods, the positions were monitored on an individual level. In this method, the portfolio as a whole is monitored. If the portfolio loss reaches above a threshold, 5% in this case, all the positions are closed. An extension of this method is also implemented to allow reopening the closed positions but only after the losses are regained. At 5% level threshold, the risk-adjusted performance of the full-portfolio stop-loss method is the best among other stop-loss methods. However, the results experience only a marginal improvement over the classic double-sort strategy and are not as expected. The 30-day VaR (99%) is noticeably improved over the classic method's.

To conclude, the double-sort strategy on commodities futures is a profitable strategy. With high return, it is advisable to include such strategy into investors' portfolio. The low correlation between this strategy and other strategies and asset classes such as equities and long-only commodity strategies advocates the risk diversification benefits of including this portfolio in any investment. The fact that the strategy is still profitable during market turmoil, such as the two recent crises, is another advantage of such strategy.

The effort to reduce the risk measures of the double-sort strategy by introducing a stop-loss did not achieve attractive results. None of the four implemented stop-loss methods improved the risk-adjusted performance of the double-sort strategy considerably. This may be due to the fact that the same measure, i.e. momentum, which is used to form the portfolio, is also used as a signal for stopping a losing position. In other words, when a commodity is included in the portfolio, it means that the commodity has shown a high past return (or a low past return if it is included in the short positions). Therefore, using the same measure to cut the position out of the portfolio is not going to give accurate results and increase the performance. Cutting the position based on that same measure will interfere with the double-sort's methodology, which is keeping the position for the holding period. Designing a different stop-loss method that uses signals other than those used to form a portfolio would an interesting and untouched field for further research.

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