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Momentum on Commodity Futures Markets: Crowds and Crashes

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Abstract

Momentum strategies with commodity futures are simple to implement and have been profitable for the past couple of decades. Nonetheless, they yield large drawdowns every once in a while. One theory that can explain these events is related to the high level of activity (crowdedness) in the strategy, which can be the cause of forced unwinding of positions after negative shocks take place due to the use of excessive leverage. Therefore, a measure of activity is used to test whether there is a relationship between returns and crowdedness. Even though the result of an analysis of momentum strategies with 12-month ranking period does not support this theory, strategies with 1-month of ranking period show that the theory might have real foundations.

1. Introduction & Motivation

Since the beginning of the 21st century, the trading of commodity-related instruments has seen an exponential increase. In fact, according to a report published in 2008 by the U.S. Commodity Futures Trading Commission (CFTC 2008), the amount of commodity instruments increased from approximately $15 billion in 2003, to over $200 billion in 2008. The exponential increase in such a short period of time is a consequence of the small *comovement* between different commodities and with other asset classes. This uncorrelation with other types of investments created an opportunity for investors to diversify and improve the performance of their portfolios (Tang and Xiong, 2012). The financialization process has been the center of a lot of discussion in regard to whether it distorts the prices of the commodities. Cheng and Xiong (2013) argue that this phenomenon has changed the commodity markets considerably.

In order to trade this value of commodity-related instruments, investors make use of financial leverage, which is a vehicle commonly used to magnify the potential return of an investment. Using financial leverage is a strategy that consists on borrowing money, usually from brokers, through margin accounts, that allows one to undertake investments that otherwise would require the use of much more of the investor's capital. In fact, the use of less capital, percentagewise, in an investment, via financial leverage, creates the opportunity for investors to embrace other trades, and to trade larger positions with less capital. Depending on the size of the margin account, on the market in question and even on the broker itself, one can invest with a broad range of leverage ratios that start from 2:1 and can go up to more than 200:1. Markets such as FOREX, in which intraday prices usually change no more than 1%, attract very high leverage ratios. On the other hand, more volatile markets (e.g. equity and commodity markets) are limited to less leverage. One should not forget that providing leverage works as lending money, and therefore, brokers are subject to credit risk just like other financial institutions and should be prepared to cover losses in the case that the client defaults. According to Zsolt Darvas (2009),

"with leveraged positions all or most of the wealth can be lost within a single day". Hence, in more volatile markets and periods, brokers provide less leverage and require more margin. In order to avoid colossal losses, hedge funds, banks and other financial institutions usually make use of several mechanisms that close positions immediately should a negative shock on the markets take place.

Following this premise, recent literature (Sokolovski, 2017) shows that high levels of activity in the same strategy (crowdedness) increase the likelihood of realizing extreme losses. Sokolovski (2017) studies this relationship specifically for the currency carry trade. This strategy consists on borrowing capital from low interest rate currencies and investing it on high interest rate currencies. This strategy, whose risk comes, in theory, solely from exchange rate, has yielded interesting sharpe ratios in the past, even though its returns present very negative skewness.

Previous research on the currency carry trade associates crashes to a succession of events that behave as a true snowball effect. These events are based on two assumptions. Firstly, it is assumed that the foreign exchange market, and particularly carry trade investors, are highly leveraged, which is very likely to happen since, as aforementioned, it is easy and cheap for investors to raise funds and trade with leverage. Secondly, previous literature assumes that traders have stop-loss mechanisms at their disposal, such as margin calls, risk management constraints and value-at-risk metrics, that when faced with unusual negative shocks, immediately close all positions. When these assumptions are verified, and a negative shock takes place, it creates a generalized movement of unwinding of positions by carry traders. The unwinding is followed by increasing pressure in the foreign exchange markets, drops in exchange rates, and more forced unwinding by traders whose stop-loss mechanisms had not triggered yet. The domino effect that is created and magnified by automatic and immediate

unwinding of positions generates, according to Sokolovski (2017), "a spiral of losses, i.e. a crash".

Based on the work developed by Sokolovski (2017), this work project studies the relationship between the activity of the momentum strategy on the nearest commodities futures contracts and crashes in the commodities markets. Similarly to the foreign exchange market, the commodities futures market is also leveraged, even though in a smaller scale, since its volatility is much higher, which prevents traders to use large leverage ratios. Therefore, since the magnitude of leverage in place is very different, the result of too much activity may also be different. Contrarily to the forex market, the commodity futures market has a particularity: in order to avoid physical delivery, investors must roll over the futures contracts before the expiration date, so they can hold the same position in the market. Every time a contract is about to expire (the nearest contract), the investor should close its position and move to the next contract (the second nearest contract). The return provided by the roll-over of the contracts depends on the term structure of the commodities future. If the price of the second nearest contract is above the price of the first, it means that the market is in contango and the investor has a negative (positive) roll yield in case he bought (sold) the contract. When the opposite happens, the market is in normal backwardation and one benefits from a positive (negative) roll yield if one bought (sold) the contract.

This Work Project proceeds as follows: Section 2 presents previous research and study on futures contracts term structure, momentum strategies with commodities futures and crowdedness measures, Section 3 explains where the data was retrieved from, how it is structured and how it will be used, Section 4 consists on a thorough explanation of the methodology implemented, Section 5 discusses the results obtained and, finally, Section 6 concludes.

2. Literature Review

According to a report published in 2008 by the Commission of the European Communities addressing the role of speculation in agricultural commodities price movements, the term structure of futures contracts can take two forms, depending on whether the futures prices is above or below the spot price: contango and normal backwardation, respectively. The term "normal backwardation" was coined by John Maynard Keynes (A Treatise on Money, 1930) as a backwardated market looked natural if one considers that farmers preferred to sell futures contracts in order to lock in the prices of the upcoming harvest. For instance, if producers are very risk-averse, they may be willing to sell futures at a price that is below the expected future spot price so that they can hedge their risk (Kolb, 1992). Producers prefer to avoid the price fluctuations during the production period due to the high volatility in the commodities markets that is caused by several reasons: the future demand is very difficult to predict, inventories are very expensive and the inelasticity of the supply response in the short-run for most commodities (Till and Gunzberg, 2005). On the other hand, non-commercial users (mostly speculators) enter the commodity futures market to catch arbitrage opportunities and profit from them (Commission for the European Communities, 2008).

Thus, while consumers enter the futures market usually only to hedge their risk, speculators and investors engage in more complex strategies and try to generate earnings. One of those strategies is momentum. Momentum is a strategy that investors pursue on the presumption that past price moves predict future price moves (Spurgin, 1999). Even though momentum has been largely studied in equity markets, there is no accurate explanation for is performance. While considered an anomaly by some authors, who believe that momentum is just a result of underreaction to news and the way investors interpret information (Barberis, Shleifer and Vishny, 1998), others state that momentum is not an anomaly (Dittmar, Kaul and Lei ,2007).

In the commodity futures market, momentum has been more and more studied in the past few years. Erb and Harvey (2006) developed a momentum strategy that, from December 1969 until May 2004, goes long on the four commodity futures with the highest previous 12-month returns and short on the four commodity futures with the worst-performing past 12-month returns. The authors compare the performance of such a performance-based portfolio to the long-only S&P-GSCI (a diversified composite index of commodity sector returns), and achieve a Sharpe ratio more than twice as high as the long-only GSCI's Sharpe ratio (0.55 and 0.25, respectively). Such a simple momentum strategy has been working as a basis for other authors to build on.

Miffre and Rallis (2007), examine 56 momentum and contrarian strategies in commodity futures markets. The authors also analyze the settlement prices of 31 US commodity futures prices over a period that starts in January, 31st 1979 and ends in September, 30th 2004. The 56 strategies (32 short-term momentum and 24 long-term contrarian) are the result of combinations of different holding periods (1, 3, 6, 12, 18, 24, 36 and 60 months) and ranking periods (1, 3, 6, 12, 24, 36, 60 months). The authors stress that the strategy requires that investors must open and monitor a margin account, pay margin calls whenever it is necessary and roll-over contracts before expiration. However, as the strategy is based on buying backwardated contracts and selling contangoed contracts, there is not much need for paying margin calls and the roll-over returns are positive most of the time. The study identifies 13 profitable momentum strategies that generate 9.38% average return a year.

More complex strategies using commodities futures have been studied recently. Triple-screen strategies, including variables as past performance, roll-yield and idiosyncratic volatility, have been proved to generate an average sharpe ratio five times higher than that of the S&P-GSCI (Fuertes, Miffre and Fernandez Perez, 2015).

Strategies like momentum, which are considerably easy to apply, attract a lot of investors and hedge funds. Therefore, due to a phenomenon called *price-pressure* (the price at which investors buy or sell an asset depends on the speed and quantity that they want to transact), it is not surprising that when the activity on momentum is very high, the markets are more prone to be destabilized. Indeed, Evans and Lyons (2002) show that order flow has impact on the prices of securities. Lou and Polk (2013) create a measure of arbitrage activity in order to analyze whether investors can have a negative effect on the market. The activity metric, which the authors name *comomentum*, consists on the high-frequency abnormal return correlation among an asset class (in this case stocks). The authors conclude that on periods when momentum is very crowded, investors may face crashes, as opposed to periods of low crowdedness, when momentum generates earnings.

Crowdedness is a concept that has been not only used in equity markets. As described previously, crowdedness has been tested on the currency carry trade (Sokolovski, 2017). The author simulates what a carry trader would do, by shorting two funding currencies and buying two investing currencies. Sokolovski assumes that these four currencies are the most likely to receive the carry trade order flow.

The procedure is followed by a 30-day rolling regression for each of the currencies, from where the author keeps the residuals, which are believed to be purged out of the U.S. and global effects (an average currency excess return of all currencies against the US Dollar is used as a predictor), leaving only the countries specific effects. Sokolovski uses the residuals of the regression to compute correlations among these set of currencies, which is chosen daily. Finally, the author calculates the spot exchange rate correlation implied crowdedness measure as an average of the correlations that were computed before.

Concluding, it is proved that between 40% to 50% of the largest drawdowns in-sample, are registered in moments that follow periods when the currency carry trade strategy is highly crowded. Furthermore, Sokolovski finds that other factors can be predictive of carry trade crashes when combined with high crowdedness. Funding illiquidity, measured by the TED spread (the difference between the three-month U.S LIBOR and the U.S T-bill interest rates), can help explain the pressure put on prices, that amplifies the initial negative shock and turns it into a crash, when elevated crowdedness is in place.

3. Data

The data used in this work project was obtained from Datastream International and comprises the daily returns of the nearest futures contracts of 31 commodities. The set of commodities includes 6 oil and gas futures (crude oil, gasoline, heating oil, natural gas, gas-oil-petroleum and propane), 14 agricultural futures (coffee, rough rice, orange juice, sugar, cocoa, milk, soybean oil, soybean meal, soybeans, corn, oats, wheat, canola and cotton), 5 metal futures (gold, silver, copper, palladium and platinum), 4 livestock futures (feeder cattle, live cattle, lean hogs and pork bellies) and the futures on rubber and lumber.

The dataset spans from January, 2nd 1985 to February, 27th 2015, which results in a sample of 7567 business days. Since not all the commodities futures contracts listed above were being traded in the beginning of the sample period, the number of commodities used in the momentum strategy has not totaled 31 during the whole sample. In fact, the number of contracts ranges from a low of 25 contracts in the beginning of the sample, to a peak of 31 in August, 12th 1997. The contracts are included in the strategy as they start being traded.

Trading the nearest futures contracts ensures that the risk of illiquidity is partially mitigated, given that these contracts have the most open interest when compared to other maturities. The

open interest tends to increase exponentially when expiration approaches, because traders are not interested in the physical delivery of the commodity. Therefore, they must roll over the contract. Hence, as expiration approaches, the number of transaction increases and provides liquidity to the market.

The returns used in this work project include the result of the roll-over of the contracts, which means that when the nearest contract is replaced by the second nearest contract, the corresponding return will reflect the term structure of the market. Thus, if the market is backwardated, then there will be a positive return from rolling the contract. On the other hand, if the market of a specific commodity is in contango, the return will be negative, since the trader will have to buy a contract that is more expensive than the one that he just got rid of.

4. Methodology

This section includes a thorough description of all methods, calculations and procedures undertaken in the process that leads to the results that are analyzed in the following section. All calculations, tests and appendices were performed in MATLAB and Microsoft Excel.

4.1. Momentum Strategy

The momentum strategy performed in this work paper follows the 12-1 momentum strategy developed by Miffre and Rallis (2007), which consists in a combination of a 12-month ranking and a 1-month holding periods.

To start with, a cumulative return of the past 12 months is computed in the end of the month for each available commodity futures. Thus, since the dataset starts in January, 2nd 1985, the first cumulative returns taken into consideration date approximately of one year after.

Once the cumulative returns are calculated, the momentum strategy buys the commodities futures contracts that outperformed in the past 12 months and sells the ones that underperformed in that same period. These contracts are selected according to a 20-80 rule, which consists on selling and buying the contracts below and above the 20th and 80th percentiles, respectively. Given that, in the beginning of the sample, the number of futures contracts available for trade was lower, the strategy selects only five contracts for each trading side. After August, 26th 1987, when the number of trading contracts broadens, the strategy goes long and short twelve contracts in total.

As aforementioned, the 12-1 momentum contemplates a holding period of one month. Indeed, the strategy is rebalanced every month, more specifically in the first business day of the month. Therefore, in the beginning of each month, the highest- and lowest-performing contracts in the past 12 months are bought or sold, and held until the beginning of the next month, when another rebalancing takes place. Although many commodities have contracts expiring every month (not all in the same day), the rebalancing date does not coincide with any of the expiration dates in particular, which means that the rebalancing may or may not occur in the same day as a contract roll-over trade. For comparison purposes, a 1-month ranking period momentum strategy is also computed.

4.2. Drawdowns

A drawdown is a measure of performance that consists on the persistent loss of value over consecutive negative returns (Sornette, 2009). Thus, a drawdown ends every time a new local maximum happens, when another drawdown starts counting. The maximum drawdown is a statistic that allows investors to determine the risk they face when considering a strategy.

Moreover, this metric can also be used for risk management purposes and work as a stop-loss mechanism.

In this work project, two different approaches are considered in order to compute the drawdowns. The first approach was the one described above. A drawdown starts in a local maximum (when a close price is higher than that of the previous day) and lasts while the daily negative returns are consecutive. Logically, it ends when a new local maximum is achieved. The second approach is different in the sense that instead of starting and ending in local maxima, a drawdown starts in an absolute maximum, and ends only when a new absolute maximum occurs. In the between, several local maxima can occur.

Sokolovski (Crowds, Crashes and the Carry Trade, 2017) describes a crash as an event that is likely to happen in a very short period of time (just a few days), forced by the consecutive unwinding of positions. Therefore, the author considers a carry trade crash the one hundred largest drawdowns in the sample.

Following the described literature, the 100 most negative drawdowns achieved with the first approach in the momentum strategy with commodities futures contracts are considered crashes. The second approach (from one absolute maximum to another), on the contrary, does not provide a clear view of what should be considered a crash. This happens because, while the first approach is able to show quick and sudden loss, which can result from intraday price changes or last for a few days, the second approach is not. The second approach allows one to observe drawdowns that can last for much longer periods, and to correlate them with the activity on the strategy during that period. Since a crash on a financial market is an almost unpredictable event, just a few days of consecutive negative returns may not be sufficient to foresee what is to come. As an example, during the financial crisis that started in mid-2007, from October, 9th 2007 until

March, 9th 2009, the S&P 500, the NASDAQ and the Dow Jones Industrial Average suffered losses of, approximately, 56.78%, 55.63% and 55.78%, respectively.

The result that comes from selecting the largest 100 drawdowns using the second approach is, however, not clear. Approximately 31% of these drawdowns belong to just one long drawdown, that lasts for more than 200 days until it reached the lowest value, which means that within a single drawdown, one can find several very negative cumulative returns. Therefore, to work around this result, the drawdowns were separated by the period when they happened. In this case, the period is six months. Thusly, the most negative drawdown in each half of every year was collected. This way, one can have a wider perspective along the whole data set.

4.3. Activity Measure

The level of activity in the commodities futures momentum strategy is hard to observe and to quantify due to the lack of data that distinguishes activity in this strategy from activity in other types of trades. Therefore, a measure computed from pairwise partial correlations of abnormal past returns, created by Lou and Polk (2013) for a stock price momentum strategy, and later adapted by Sokolovski (2017) for the currency carry trade, is a reliable proxy for the crowdedness in the commodity futures momentum. This method, called *comomentum* by the authors, is based on the price pressure premise that the price at which investors buy and sell securities depends on the order flow.

Adapting the methodology of Sokolovski to the commodity futures market, at the end of each day, all the tradable futures contracts are sorted performancewise (past 12 months cumulative returns). The top and bottom futures are then selected, similarly to what is done in the momentum strategy, because when investors engaging in the momentum strategy tilt their allocations, they are more likely to do so towards the best- and worst-performing futures

contracts. Therefore, to replicate the allocation changes as close as possible, the activity measure includes eight futures contracts, the best and worst four.

The selected commodities futures are then subject to separate ordinary least squares regressions, over the returns of the 30 previous days.

$$ret_t^i = \alpha + \beta_{Mkt}Mkt_t + e_t^i$$

where ret_t^i corresponds to the returns of a commodity i on the trading days *[t-30, t-1]*, Mkt_t represents the average of the returns of the selected commodities in the same period, and e_t^i consists on the regression's residuals.

According to Sokolovski's methodology, one should keep the residuals in order to compute correlations among all the selected commodities. Since eight futures are selected at a time, 28 (pairwise) correlations are computed on every trading day: six correlations between the contracts that compose the top-4, another six correlations for the contracts that compose the bottom-4, and sixteen cross-correlations (between top and bottom contracts).

A pairwise correlation looks as follows:

$$corr_t^{W_iW_j} = Corr\left(e^{W_i}, e^{W_j}\right) \qquad\qquad corr_t^{L_iL_j} = Corr\left(e^{L_i}, e^{L_j}\right)$$

$$corr_t^{W_iL_i} = Corr\left(e^{W_i}, e^{L_i}\right) \qquad\qquad corr_t^{W_iL_j} = Corr\left(e^{W_i}, e^{L_j}\right)$$

where W and L stand for winners and losers, respectively, $i,j = [1,4]$, $i \neq j$, and $corr_t^{W_iL_j}$ corresponds to the correlation between a top and bottom futures contract from *t-30* to *t-1*.

Once the correlations are obtained, one should follow the methodology of Sokolovski of averaging them all:

$$Crowdedness_t^{Comdts} = \frac{corr_t^{W_iW_j} + corr_t^{L_iL_j} - corr_t^{W_iL_i} - corr_t^{W_iL_j}}{28}$$

where the variables are defined as before. The cross correlations appear with a negative sign because the order flow is to buy winners and to sell losers, which puts opposite pressures on both of their prices.

5. Results

This chapter follows the same structure as the previous one, addressing the Momentum Strategy, Drawdowns and, finally, Activity Measure. All the appendices mentioned in this section can be found in the end of the report.

5.1. Momentum Strategy

As mentioned before, the momentum strategy sells the contracts below the 20th percentile and buys the contracts above the 80th percentile, following a 12-1 structure (12-month ranking period and 1-month holding period). The results of this strategy are summarized in Table 1, alongside the results of the winners and losers' portfolios that follow the same construction mechanism. The equal-weight momentum strategy has an annualized return of 8.74%, which is between that of the Winners and Losers' portfolios (10.01% and 5.45%, respectively). However, when the portfolios are compared in terms of risk-to-return, the momentum strategy is more appealing: its sharpe ratio of 0.81 is much higher than the other two strategies' (0.53 and 0.34). In terms of the normality of the returns' distribution, according to George, D., and Mallery, M. (2010), one considers as normally distributed a set of data with skewness and excess kurtosis between -2 and +2. The returns of the momentum strategy, however, have skewness of -0.16 and excess kurtosis of 2.38, which means that the distribution of the returns is non-normal. The distribution of the daily returns is shown in Figure 1. In fact, the curve is slightly left-skewed and has fatter tails than a normal distribution. When these two features are

combined, the probability of having sudden very negative returns is higher. This is in accordance with the fact that momentum, which has been shown across various asset classes, is unattractive to investors that prefer to avoid negative skewness and positive excess kurtosis (Barroso and Santa-Clara, 2015).

5.2. Drawdowns

As mentioned before, two approaches were considered when computing drawdowns in the momentum strategy. The first approach consisted on the accumulated loss over consecutive daily negative returns. In this case, the maximum drawdown occurred in October, 24th 1990 and consisted on a loss of approximately 10.92%. This drawdown, which lasted for five days, was partially caused by the combined loss in several commodities, most of them in the energy sector. Although this approach is very useful in order to capture sudden and meaningful losses (i.e. crashes) in the momentum strategy, it is does not provide enough information on why these losses occur, as they can be the result of mere speculation. The evolution of the drawdowns following this approach are represented in Figure 2.

The second approach, on the other hand, provides more insight on macroeconomic imbalances between demand and supply, because the losses of the strategy can be seen more as cascades than as abrupt events. Therefore, drawdowns in the 12-1 momentum strategy show long-term events and crises on commodities markets. As shown in Figure 3, the strategy suffers several very negative losses along the almost 30 years of trading. The first large drawdown (the second most negative in the whole dataset) starts in April, 1st of 1986 and reaches its bottom on the January, 2nd of 1987, when the accumulated loss equaled 18.08%. This loss is mainly associated to a surplus of oil in the market commonly named as the Oil Glut, caused by disagreements among OPEC countries, which flooded the market with excessive production of oil. The

continuous falling price of crude oil created a perfect opportunity to sell contracts. However, the market turned due to a new agreement on production quotas and prices started to increase. Thus, while prices increased, the signal was to sell contracts, which is explained by the fact that the strategy has a 12-month ranking period. If one considers a 1-month ranking period, the result is different, as the strategy adapts to the turn in the macroeconomic conditions faster.

In 2003, another large drawdown (both in duration and magnitude) starts due a sudden crash in the prices of the energy sector commodities in the middle of a continuous and steady price increase. In fact, in less than two months, the price of crude oil decreased more than 33.19%.

The largest drawdown in the sample starts in July 2008 and ends in June 2009, and consists on a loss of approximately 19.38%. After an unsteady but prolonged increase in prices of crude oil, as well as other energy commodities, from 2002 until mid-2008 (from approximately 20 dollars per barrel to 140 dollars per barrel), prices consistently fell to values below 34 dollars in 2009, which means that strong signals that suggested that buying energy commodities came out to yield disastrous results. Once again, a momentum strategy with a shorter ranking period is much faster in adapting to sudden turns in price trends.

Figure 4 shows the cumulative returns of the 12-1 momentum strategy, 1-1 momentum strategy, long-only and short-only portfolios.

5.3. Activity Measure

Once the measure of crowdedness has been calculated, whose evolution is represented in Figure 5, it is possible to address the main purpose of the report: to check the relationship between commodity futures momentum crashes and the level of activity. In order to do so, the methodology of Sokolovski (2017) is closely followed. First, all values of activity during the whole sample period are separated into quintiles. Quintile 1 contains the lowest levels of

momentum activity, while Quintile 5 is composed of the highest values. Then, the probability of a crash (defined as an accumulated consecutive loss that makes the top 100 of the largest drawdowns) being associated to each quintile is calculated. The Panel A of Table 2 shows the percentage of Top 20, 40, 60, 80 and 100 crashes in each quintile of activity level in the 12-1 momentum strategy. It is visible that the higher the magnitude of a crash, the lower the level of activity: for example, only 10% of the Top 20 crashes are associated with the highest values of crowdedness, while for the Top 100 crashes that value is 18%. Also, the probability that the lowest values of activity (Quintile 1) are in the Top 20 crashes is higher than in the Top 100 (35% and 27%, respectively). Furthermore, one can see in the second column that the average value of activity is also lower for Top 20 crashes (-0.10) than for Top 100 crashes (-0.08). However, when 1-1 momentum is considered, the results are opposite. The probability that Top 20 crashes have higher activity levels than that of Top 100 crashes is confirmed (60% against 33%). For low levels of activity, the probability is the same for both (5%). These results can be seen in Panel B of Table 2.

In order to confirm that the chance that lower values of activity occur when crashes are greater is higher than when there are no massive losses, a goodness-of-fit test is performed. Assuming that the construction of the activity quintiles is distributed uniformly, means that any subsample that is randomly taken is also uniformly distributed. Therefore, if one takes a subsample based on the returns of the strategy, it is to expect that the subsample of activity levels is, once again, uniformly distributed (Sokolovski, 2017). To test whether this assumption can be held, one can perform a Kolmogorov-Smirnov (KS) test, for each subsample individually. The test statistic consists on the maximum distance between the empirical cumulative distribution function (ECDF) and a hypothetical cumulative distribution function (CDF). The KS test's null and alternative hypotheses are, respectively:

$$H_0: F(Q) \; = \; U(Q), \text{the subsample is uniformly distributed}$$

$$H_A: F(Q) \neq U(Q), \text{ the subsample is not uniformly distributed,}$$

where Q stands for quintile (1 to 5), *F(Q)* is the cumulative distribution of the quintiles and *U(Q)* is the normal uniform distribution.

The results of the test can be seen in the last two columns of Table 2. Even though the null hypothesis cannot be rejected for a 5% significance level for the Top 20, 40 and 60 crashes, it is rejected for both Top 80 and Top 100 crashes, which means that for the latter, the assumption that there is no relationship between activity in momentum strategy and momentum returns is not valid.

For the 1-1 momentum strategy, the null hypothesis is rejected for the Top 100 crashes, which means that the same conclusion can be drawn.

6. Conclusion

Even though momentum with commodity futures has yielded a steady and consistent profit over the past 30 years, the strategy has suffered several large losses along the way. One of the reasons that can be behind these crashes is the level of activity (crowdedness) that goes on the strategy. Theories proposed in the past, affirm that highly crowded markets can be the cause of colossal crashes because of a phenomenon of unwinding positions that is triggered by an initial larger than usual loss, which is widely amplified due to mechanisms such as stop-loss orders, risk management constraints and value-at-risk metrics that, through price pressure, create a snow-ball effect.

However, this is not the case for 12-1 momentum in commodity markets. In fact, for a momentum that contemplates a 12-month ranking period and a 1-month holding period, 35% of the Top 20 of largest crashes occur when the level of activity is at its minimum. Furthermore,

only 10% occur when the activity level is at its peak. On the other hand, of the Top 100 drawdowns, 27% occur in periods of low activity (8 percentage points less), and 18% in periods of high crowdedness (8 p.p. more). Although the unwinding phenomenon is not confirmed by the results in 12-1 momentum, it happens in 1-1 momentum.

Therefore, one can conclude that momentum strategies deal with crowdedness in different ways. While high activity means less likelihood of crashes for a strategy that entails 12 months of ranking period, for a 1-month ranking period momentum, high levels of crowdedness means the opposite: a greater likelihood of facing crashes, due to the sudden but strong unwinding of positions.

This report builds on the works of Lou and Polk (2013) and Sokolovski (2017) which analyze the relationship between crowdedness and the performance of financial markets (equity and forex markets, respectively).

As a suggestion for future research, it would be interesting to assess how activity levels affect the returns of a momentum strategy, while controlling for commodity futures illiquidity, funding illiquidity (e.g. through the TED spread) and for volatility.

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Appendix

Figure 1: Distribution of 12-1 Momentum Daily Returns

This graph presents the distribution of momentum daily returns. The x-axis represents the daily returns, while the y-axis shows the percentage of each daily return occurring during the whole dataset.
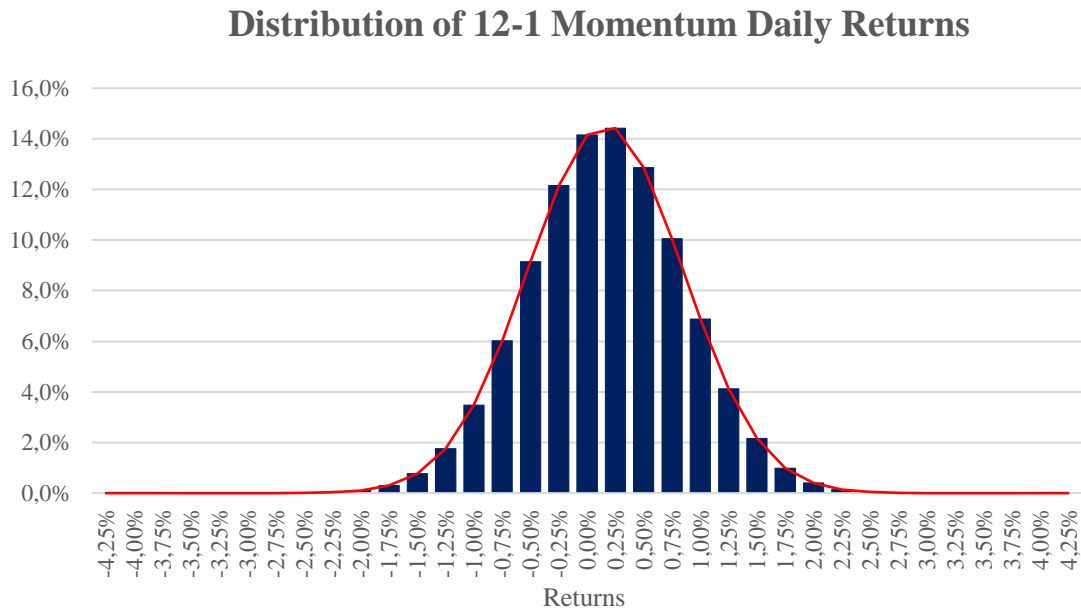

Distribution of 12-1 Momentum Daily Returns

Figure 2: Drawdowns computed according to the 1st approach

Drawdowns 1st Approach

Figure 3: Drawdowns computed according to the 2nd approach

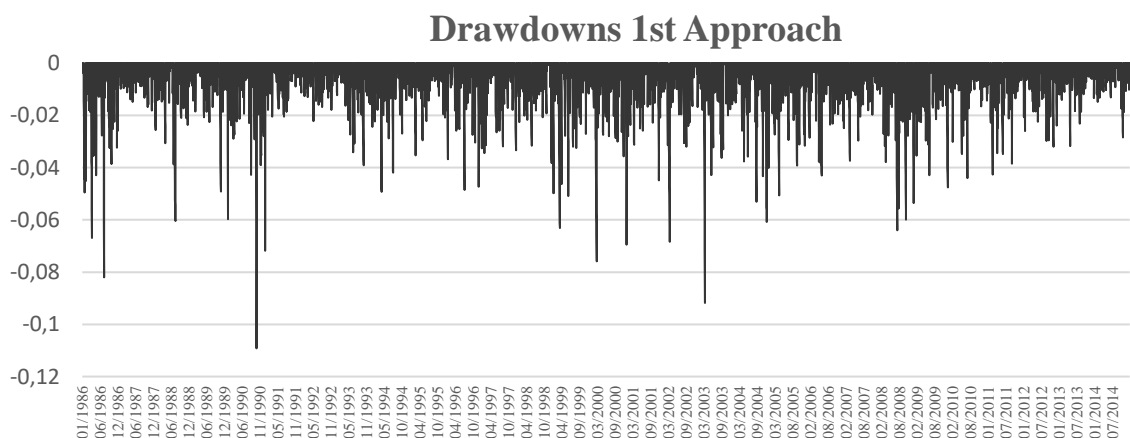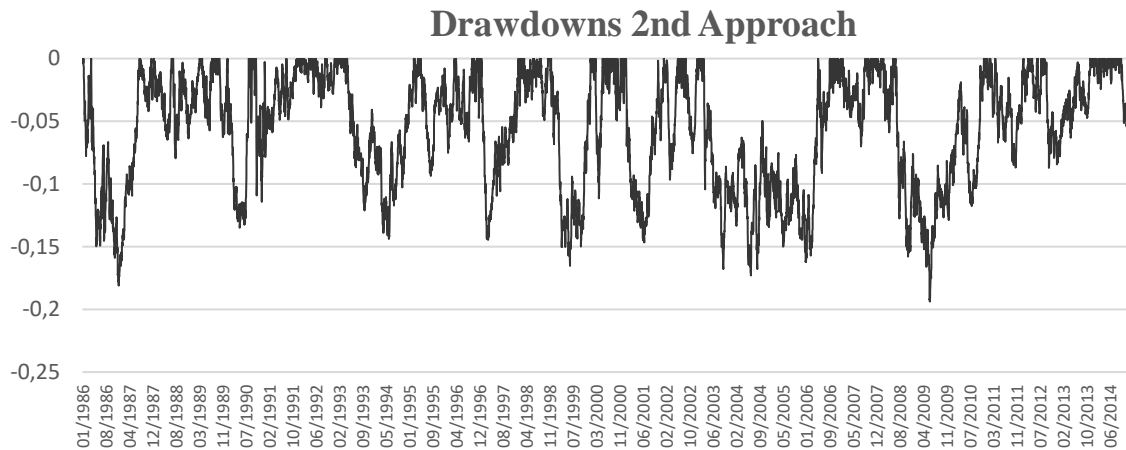**Drawdowns 2nd Approach**

Figure 4: Cumulative Returns

This graph plots the cumulative return of 4 strategies: Long-only (Winners), Short-only (Losers), 12-month ranking and 1-month holding periods momentum, and 1-month ranking and holding periods. All strategies start with 1\$ in 01/1986. The data goes until the end of 12/2014.
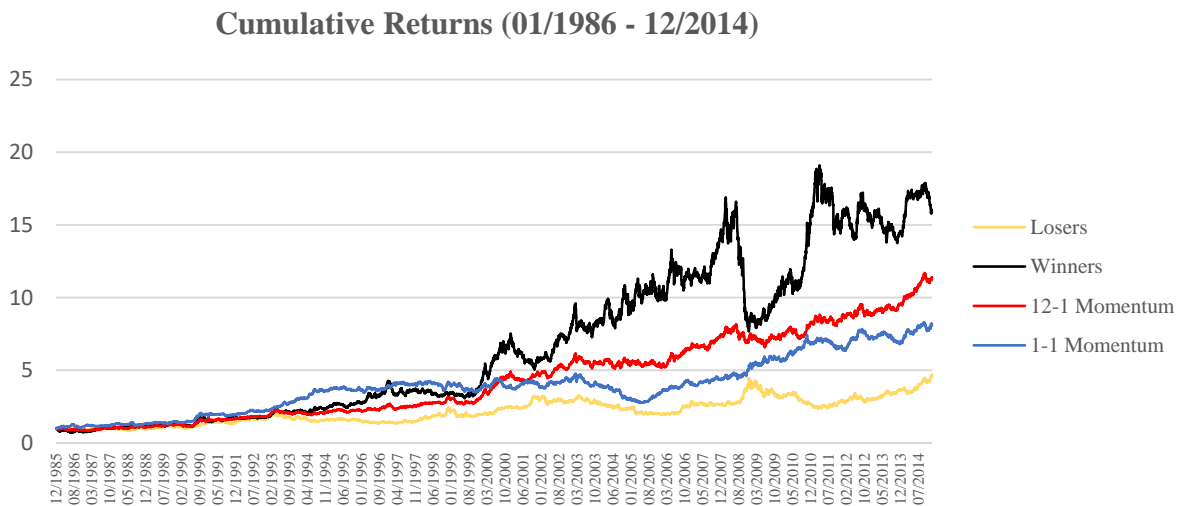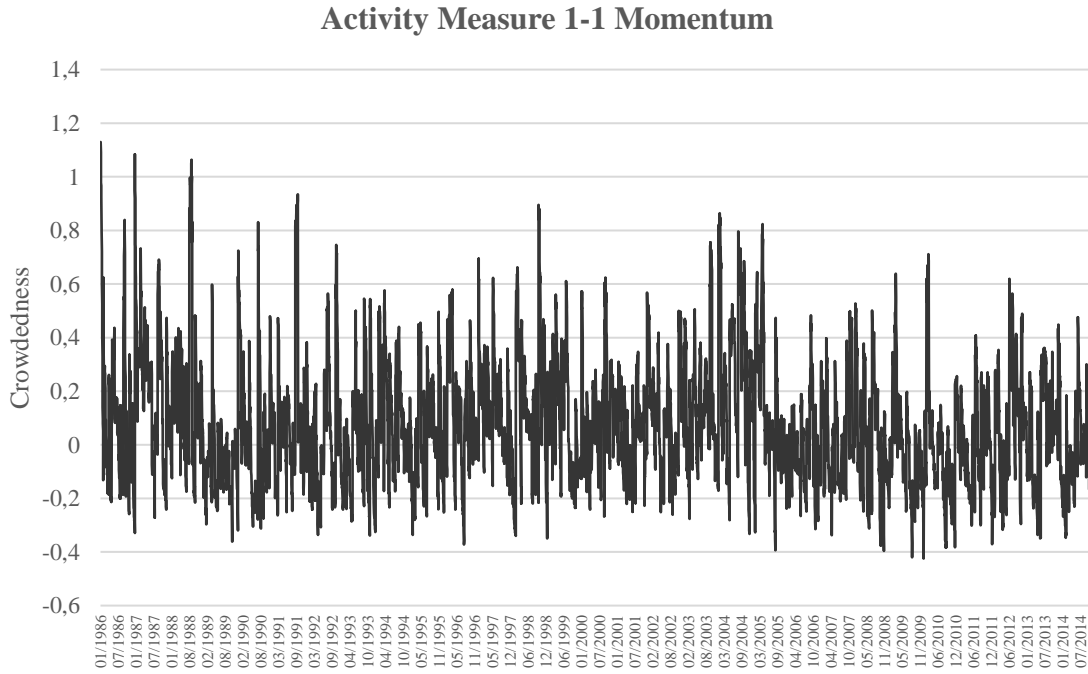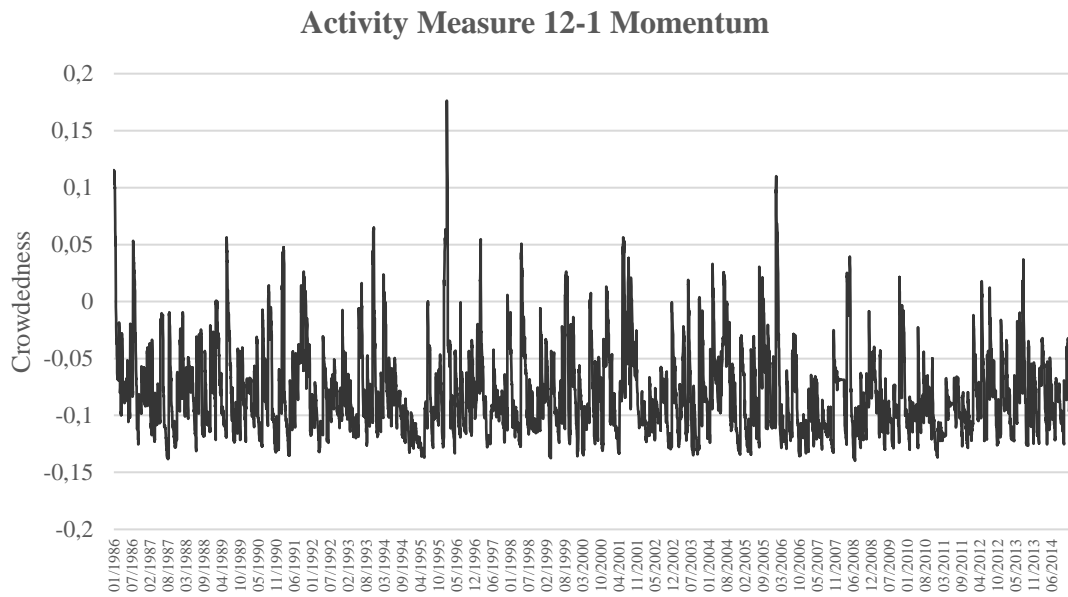
Cumulative Returns (01/1986 - 12/2014)

Figure 5: Evolution of Activity level

Activity Measure 12-1 Momentum

Activity Measure 1-1 Momentum

Table 1: Summary Statistics of 12-1 Commodity Futures Momentum

	Momentum	Winners	Losers
Mean Return	0.036%	0.045%	0.026%
Avg Annual Return	8.74%	10.01%	5.45%
Std Dev	10.78%	18.86%	15.95%
Sharpe Ratio	0.81	0.53	0.34
Skewness	-0.16	-0.35	-0.09
Excess Kurtosis	2.38	4.58	2.35
AC(1)	0.075	0.096	0.037
Max (%)	3.56%	7.49%	5.85%
Min (%)	-6.05%	-12.83%	-6.09%

Table 2: Momentum crashes and Activity level quintiles

4 COMDTS

		Avg	Q1	Q2	Q3	Q4	Q5	KS	CV ($\alpha = 0.05$)
	Top 20	-0.10	0.35	0.10	0.30	0.15	0.10	0.16	0.29
	Top 40	-0.09	0.30	0.10	0.30	0.18	0.13	0.17	0.21
Panel A:	Top 60	-0.09	0.33	0.08	0.25	0.20	0.13	0.14	0.18
	Top 80	-0.09	0.30	0.16	0.21	0.16	0.16	0.17	0.15
	Top 100	-0.08	0.27	0.15	0.25	0.15	0.18	0.17	0.14

		Avg	Q1	Q2	Q3	Q4	Q5	KS	CV ($\alpha = 0.1$)
	Top 20	0.10	0.05	0.00	0.00	0.20	0.60	0.25	0.26
	Top 40	0.20	0.05	0.03	0.03	0.10	0.43	0.15	0.19
Panel B:	Top 60	0.25	0.07	0.02	0.02	0.07	0.35	0.08	0.16
	Top 80	0.26	0.05	0.01	0.03	0.06	0.36	0.13	0.14
	Top 100	0.26	0.05	0.02	0.03	0.06	0.33	0.13	0.12