

CAN INDIVIDUAL INVESTORS BENEFIT FROM TECHNICAL ANALYSIS IN MARKETS OF SOFT COMMODITIES? EMPIRICAL STUDY FOR 2010–2018

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ABSTRACT

After the 2008 financial crisis, many investors diversified their portfolios with different commodities, including the so-called softs. This paper aims to answer the question of whether individual investors can benefit from technical analysis on soft commodity markets. The empirical study is based on daily quotations of six soft commodities: coffee, cocoa, sugar, cotton, rubber and frozen concentrated orange juice from 2010 to 2018, and investigates the profitability of applying indicators and oscillators based on moving averages with different length. The results show that the application of five-day simple and weighted moving averages and momentum oscillators was most effective, providing positive returns in five out of six soft commodities markets.

Key words: soft commodities, technical analysis, profitability of technical rules

JEL codes: G11, G14

INTRODUCTION

Technical analysis is a method of forecasting price movements using past prices, volume and/or open interest. It is based on the assumption that markets are driven more by psychological factors than fundamental values. Its advocates are of the opinion that commodity prices reflect not only the underlying “value” of the commodity, but also the hopes and concerns of market participants. If the emotional attitude of investors does not change, then in a certain set of circumstances, investors will behave in a similar way to how they used to do in the past. As a result it is very likely that price moves will be the same. In other words: “history tends to repeat itself” [Lhabitant 2008, p. 392].

Pring provides a more specific definition. According to him, “the technical approach to investment is

essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.” [Pring 2002, p. 2].

Geman quotes another definition, originally developed by Perfetti in 1992, that “technical analysis is the ability to identify trend changes at any early stage and to maintain an investment position until the weight of evidence indicates that the trend has reversed” [Geman 2007, p. 163]. It is worth noting that technical analysis is not aimed at forecasting trends in the economy nor at assessing the attitudes of investors toward those changes. Rather, it is focused on identifying turning points in market performance.

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The history of technical analysis dates back to at least the 18th century, when the Japanese developed a technique that is today known as ‘candlestick charting’. It was not introduced to the West until the 1970s [Park and Irwin 2008]. What is more, technical analysis has a long history and a widespread use in commodity markets. The technical approach to investment in commodity markets also relies on the same premise that prices move in trends determined by changing attitudes of investors toward a number of variables, including factors that dictate price movements in both physical and futures markets.

Over the years, numerous empirical studies have investigated the profitability of technical rules in a variety of commodity markets. For example, in his pioneering work, Smidt [1965] surveyed amateur traders in U.S. commodity futures markets and found that over half of the respondents used charts exclusively or moderately in order to identify trends. In more recent contribution, Miffre and Rallis [2007] present evidence that trend-following strategies perform well for commodities, consistent with previous results on the equity markets. Similar findings are obtained in Erb and Harvey [2006], Fuertes et al. [2008], Szakamary et al. [2010], Górska and Krawiec [2011], or Zaremba [2015]. The studies mostly focus on markets of gold, oil and some agriculturals, including single soft commodities, most often cocoa or coffee, and sometimes sugar. This paper investigates six basic soft commodities: coffee, cocoa, sugar, cotton, rubber and frozen concentrated orange juice. The empirical analysis covers the period from 2010 to 2018 and is aimed at assessing the profitability of investment strategies based on moving averages and oscillators applied in these markets.

METHODOLOGY

A first simple and intuitive approach to gather evidence that commodities exhibit persistent trends is to compute autocorrelation of returns of order h , that is:

$$\hat{\rho}_h = \frac{\text{cov}(r_t, r_{t-h})}{V(r_t)} \quad (1)$$

where:

$\text{cov}(\cdot, \cdot)$ – covariance,

$V(\cdot)$ – variance.

If $\hat{\rho}_h$ is positive and significant at 5% risk level, this provides evidence that a given commodity exhibits persistence. On the contrary, if $\hat{\rho}_h$ is negative and significant, the commodity under consideration has a mean-reverting behavior, rapidly correcting its trajectory in case of a large positive or negative return. An asset or commodity with persistent returns will stand a higher chance of being affected by trends. When it goes through a shock, this shock will have long-lasting effects on the returns themselves. In other words: an asset with positively autocorrelated returns will stand a greater chance of displaying a performance of a similar sign over the following periods [Chevallier and Ielpo 2013].

Instead of testing the statistical significance of any individual autocorrelation coefficient, we can test the joint hypothesis that all the $\hat{\rho}_h$ up to certain lags are simultaneously equal to zero. This can be done by using the statistic developed by Box and Pierce [1970]. In 1978 this statistic was modified by Ljung and Box. The Ljung–Box (LB) statistic is defined as:

$$LB = n(n+2) \sum_{h=1}^m \frac{\hat{\rho}_h^2}{n-h} \quad (2)$$

where:

n – sample size,

m – lag length.

In large samples LB statistic follows chi-square distribution with m degrees of freedom [Ljung and Box 1978]. According to Gujarati, “the LB statistic has been found to have better (more powerful in the statistical sense) small-sample properties than the Box–Pierce statistic” [Gujarati 2003, p. 813].

The basics of trend-following investment approaches should push investors to hold a long position (respectively short) into commodities with a positive (negative) past performance. Despite the simplicity of the approach, there are some important issues that should be considered. One of them is the horizon over which to compute the past performance of each asset – that is the past momentum. However, investors can choose between several alternative investment strategies that track this momentum effect in commodities. They are filters, moving averages or channel breakouts, momentum oscillators, etc.

Indicators are one of the most frequently used technical analysis tools. In simplified terms, it can be stated that technical indicators are mathematical formulas for which data is used to determine the changes in prices of stock exchanges and the volume of trading. The result of such an algorithm is the forecast of the trend as well as turning points on the market [Achelis 1998]. Most often, the indicators are presented separately or together with price on the charts. An appropriate intersection or positioning of specific lines relative to each other on the chart generates a buy or sell signal that should be reflected in investment decisions.

The faster the signals of market changes can be read, the greater the value an indicator has for an investor. As with charts, one can create indicators for data with a different time horizon. They constitute quite a large group of tools. Experts divide technical indicators, among others, into trend indicators and oscillators. The former are tools mainly used to identify a trend. In the literature, this group of tools is referred to as trend-following indicators. This is due to the fact that they are usually lagging behind the trend, i.e. they change direction after a trend change. They work better for long- and medium-term trends than for horizontal trends. On a flat market, they often give incorrect signals about turning points. For long- and medium-term trends, these indicators can confirm the trend, but also identify divergence, which is a warning signal for investors. This group of indicators includes moving averages (simple moving average, weighted average, exponential average) and MACD (moving average convergence/divergence).

Indicators that catch turning points more effectively are oscillators. They react simultaneously or even overtake price changes. Their task is to study the speed of these changes and generate signals informing about short-term changes in trends. That is why they work well in horizontal trends as well as in markets with high price volatility. This group of investment tools includes, among others, momentum and CCI (commodity channel index).

Moving averages (MA) are one of the most popular technical analysis tools. This average is a function that can be written by the formula [Wang et al. 2014]:

$$MA_t = \frac{1}{n} \sum_{i=t-n+1}^t p_i \quad (3)$$

where:

- n – number of days for which the moving average is calculated,
- p_i – today's price.

There are two objections to the simple moving average which question its usefulness. The first is that it is incorrect to give equal weights to data included in the average. The second plea relates to taking into account in the simple average only the period it covers, while the exchange rate may depend on a larger time horizon. The first complaint can be refuted by building a weighted average. As a result, subsequent observations can be assigned appropriate weights, e.g. the oldest observation will have a weight of one, and subsequent observations will have one more than the previous one. As a result, the structure will look like this:

$$\overline{MA}_t = \sum_{i=t-n+1}^t w_i \cdot p_i \quad (4)$$

where:

$$w_i = \frac{2i}{n(n+1)}$$

Both averages do not cover the entire study period.

In addition to simple moving averages, where all prices have the same weight and weighted average, the exponential moving average (EMA), which covers the entire study period, is used by market participants [Šonje et al. 2011]:

$$EMA_t = (p_t - EMA_{t-1})K + EMA_{t-1} \quad (5)$$

where:

K is the weight of the most recent observation

$$K = \frac{2}{n+1}$$

The most recent price, which enters the calculation last, has the greatest weight in calculation of averages, while the oldest price has the least weight. Hence, EMA reflects the current market situation more objectively than simple moving averages where the oldest and the latest price receive the same weight.

Moving averages form a large group of technical indicators that allow identification of a trend. It is difficult to indicate which average is the most effective because it depends on the market conditions. The most common uses of moving averages are to identify the trend direction and to determine levels of support and resistance. Although moving averages are useful in themselves, they also form the basis for other technical indicators such as the Moving Average Convergence Divergence (MACD).

MACD is a trend-following momentum indicator that shows the relationship between two moving averages of a security's price and triggers buy and sell signals for investors. Many research papers on technical analysis apply standard lengths for averages used in MACD [Apirine 2017, Wang and Kim 2018, Borowski and Pruchnicka-Grabias 2019]. MACD construction requires three exponential moving averages (EMA) to identify the continuation or reversal of a trend. It is generally accepted that the periods are 12 and 26 days for generating the first indicator:

$$MACD = EMA_{12\text{-day closing prices}} - EMA_{26\text{-day closing prices}} \quad (6)$$

The second indicator (signal line) is applying EMA to smooth the first indicator. The standard day setting for signal line is 9:

$$Signal = EMA_{9\text{-day MACD}} \quad (7)$$

A buy signal is generated when the MACD indicator (more volatile) crosses the *Signal* (less volatile one) from beneath. The sales signal is generated when the opposite condition occurs: when MACD indicator crosses *Signal* indicator from above.

Momentum is another of the basic tools from the oscillator group for measuring impetus. It measures the degree of buying out or selling out of the market. The design of this indicator is simple. In order to determine it, we use the following formula:

$$Mtm_k = p_t - p_{t-k} \quad (8)$$

where:

p_t – price at moment t ,

p_{t-k} – price from before k sessions from t .

It can be seen that the algorithm consists of counting the differences that inform how the price of the stock changes in relation to the price from a few days ago. As in the case of most indicators, here too one should consider the choice of parameter k . Of course, there is no universal size for this parameter. One often proposed value is a 10-day price comparison period. It should be remembered that higher values of this parameter will smooth the indicator, which will result in a smaller number of buy or sell signals. Smaller values will cause larger fluctuations of the indicator, which will generate more transaction signals.

RESULTS

In the first step of the research, to test whether soft commodities returns are independent, we plot the sample autocorrelation functions (ACFs) in the figure. Although some autocorrelations are statistically different from zero at the 5% level (e.g. at lags 18, 20, 21 and 24 for coffee; at lags 1 and 28 for cocoa, etc.), there is no systematic pattern of autocorrelations. To investigate it further, we compute the Ljung–Box test statistic of the joint null hypothesis that all of the first 5, 10, 20, and 30 autocorrelations are zero. The results obtained are given in Table 1. They show that regardless of the number of lags, we find statistically significant autocorrelation for cotton, frozen concentrated orange juice, and rubber returns.

In the second step of the research, standard (i.e. most commonly used) indicators with different parameters, recommended among others by Tarczyński [1997], Murphy [1998], Czekaj et al. [2001], Witkowska et al. [2008], Šonje et al. [2011], Wang et al. [2014] or Wang and Kim [2018], are calculated. They are:

- simple moving average: 5, 10, 20, 50 and 200 days,
- weighted moving average: 5, 10, 20, 50 and 200 days,
- exponential moving average: 5, 10, 20, 50 and 200 days,
- MACD: 8; 17; 9 and 12; 26; 9,
- momentum: 5; 9, 10; 9, 20; 9, 50; 9 and 200; 9.

A summary of the most important simulation results carried out for individual indicators and oscillators is given in Table 2, which contains information

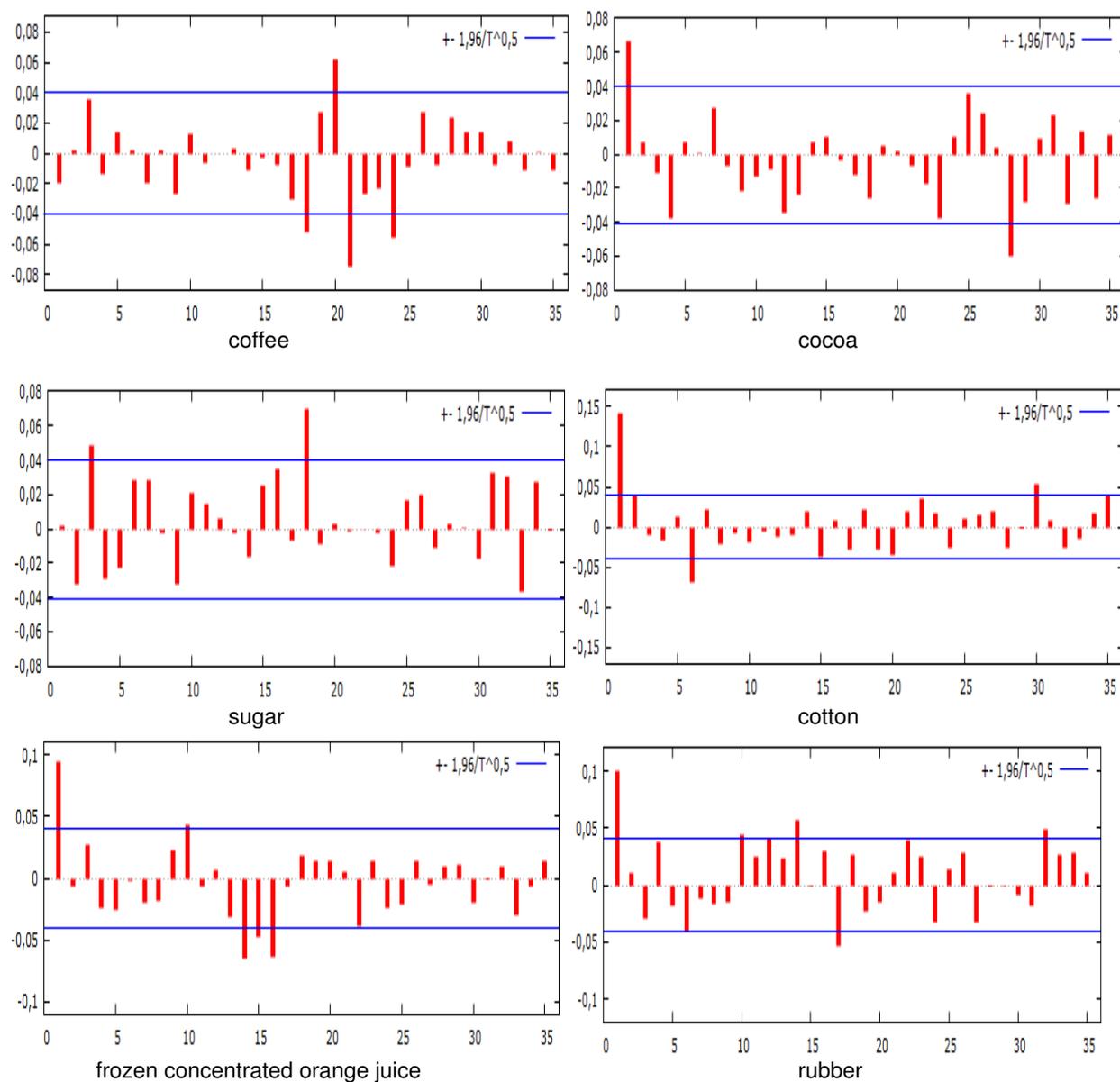


Fig. Sample autocorrelation functions (ACFs) for logarithmic returns of soft commodities
 Source: Authors' own elaboration.

Table 1. Values of LB statistic for logarithmic returns of soft commodities

Commodity	Number of lags			
	5	10	20	30
Coffee	4.8438	7.8191	27.9081	55.8324*
Cocoa	14.3169*	17.8103	24.5074	44.1068
Sugar	11.3304	18.6346	36.0812*	39.8390
Cotton	52.4109*	66.3855*	79.3478*	95.5148*
Frozen concentrated orange juice	25.3462*	32.6107*	62.0841*	70.4830*
Rubber	30.2267*	40.2175*	66.7658*	80.1670*

*Denotes rejection of null hypothesis at 0.05 level.

Source: Authors' own calculations.

Table 2. Returns obtained as a result of using specific investment strategies based on indicators and oscillators in the markets of soft commodities (%)

Indicator or oscillator	Parameter	Commodity					
		coffee	cocoa	sugar	cotton	frozen concentrated orange juice	rubber
Simple moving average	5	25.00	10.83	-36.67	140.54	499.05	243.84
	10	-6.76	2.28	-32.30	80.04	154.08	157.18
	20	-34.94	-14.69	11.91	5.10	44.53	150.61
	50	2.44	-25.83	-15.36	-9.20	6.23	105.87
	200	8.73	-46.03	-41.71	-26.75	-29.87	-13.72
Weighted moving average	5	33.03	6.51	-21.01	183.07	587.31	195.46
	10	-11.31	1.88	-9.62	86.67	163.03	116.69
	20	-27.67	-22.72	19.01	27.93	76.60	108.07
	50	-25.02	-37.02	-2.99	-17.76	18.85	130.49
	200	-29.11	-18.30	-28.18	2.35	8.43	-11.81
Exponential moving average	5	13.12	-10.29	-31.95	121.08	229.38	117.20
	10	-11.99	-7.93	-11.34	91.15	211.23	131.01
	20	-43.95	4.78	8.18	-4.33	43.87	225.05
	50	-17.52	-31.95	-10.01	26.47	54.65	85.72
	200	37.77	-37.75	-25.61	22.16	-11.33	-4.74
MACD	8; 17; 9	-18.53	-14.66	-53.01	31.67	112.29	20.19
	12; 26; 9	-47.17	4.95	-22.69	-16.71	30.12	87.71
Momentum	5; 9	28.96	55.40	-50.54	182.02	367.13	73.36
	10; 9	38.10	57.40	-62.93	65.40	501.29	1.63
	20; 9	103.29	18.77	-12.56	75.97	185.27	26.59
	50; 9	-7.19	34.16	21.30	43.42	25.01	24.98
	200; 9	-0.64	42.35	-22.70	-5.14	13.88	-48.65

Source: Authors' own calculations.

on the rates of return obtained as a result of the use of appropriate investment strategies based on moving averages and oscillators with the above-mentioned parameter values.

Results given in Table 2 show that the application of the strategies was the most effective in the market of frozen concentrated orange juice, where 20 out of 22 strategies provided positive returns (the highest one

was generated by the 5-day weighted moving average and it is the highest return of all positive returns obtained in six soft commodities markets) and the least effective – in the market of sugar, where only 4 out of 22 strategies brought about positive returns (the highest one was obtained through application of momentum – 50; 9). Nevertheless, in the case of the coffee market, the highest positive return was generated by

momentum (20; 9), in the case of cocoa – by momentum (10; 9), in the case of sugar – momentum (50; 9), in the case of cotton – 5-day weighted moving average and for rubber – a 5-day simple moving average. We can also notice that the most effective was the application of 5-day simple moving and weighted moving averages, as well as of momentum oscillators, providing positive returns in 5 out of 6 soft commodities markets. Thus, although from an individual investor's perspective it is convenient to have moving averages that will rarely give signals to buy or sell and keep her/him within the trend as long as possible, here 200-day simple, weighted and exponential moving averages as well as momentum (200; 9) performed the worst. In most cases they brought positive returns only in 2 out of 6 soft commodities markets.

CONCLUDING REMARKS

Technical analysis in commodity markets is generally no different from that in any other financial markets. The strategies that are used to trade those markets can be transposed to trade commodity stocks, commodity futures and options, or commodity exchange traded funds (ETFs). The tools of technical analysis can also be used to predict commodity spot price movements. The basic assumption of technical analysis is that the fundamentals are already reflected in the prices and there is no need to focus on reviewing research reports and other fundamental factors, such as inventories, crops, weather, etc. Instead, it is reasonable to examine prices, volumes, and some patterns in commodity market performance in a certain time frame. By studying such recurring patterns, investors can get an idea of how the market will probably trade in the future [Balarie 2007].

Technical analysis contains a bundle of different trading strategies and forecasting techniques such as moving averages, technical breakouts, candlestick patterns, or other technical indicators. Our paper focuses on the performance of moving averages and oscillators in markets of six basic soft commodities, i.e. coffee, cocoa, sugar, cotton, rubber and frozen concentrated orange juice in the period from 2010 to 2018. The results obtained show that the application of the strategies was the most effective in the market

of frozen concentrated orange juice, where 20 out of 22 strategies provided positive returns. What is more, the most effective strategies were 5-day simple moving and weighted moving averages, as well as momentum oscillators, providing positive returns in 5 out of 6 soft commodities markets. Thus we can conclude that in the period under consideration, individual investors could benefit from technical analysis in soft commodities markets. This contradicts the efficient market hypothesis, according to which all information would already be incorporated in the prices, and the presence of synchronized changes and trends in the behavior of different commodity prices should not persist.

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CZY INWESTORZY INDYWIDUALNI MOGĄ OSIĄGAĆ ZYSKI NA RYNKACH *SOFT COMMODITIES* NA PODSTAWIE ANALIZY TECHNICZNEJ? WERYFIKACJA EMPIRYCZNA DLA OKRESU 2010–2018

STRESZCZENIE

Od czasu kryzysu finansowego z 2008 roku wielu inwestorów dywersyfikuje swoje portfele poprzez włączenie do nich towarów w tym tzw. *soft commodities*. Celem niniejszej pracy jest odpowiedź na pytanie, czy inwestorzy indywidualni mogą osiągać zyski w wyniku zastosowania analizy technicznej na rynkach *soft commodities*. Podstawę przeprowadzonych badań empirycznych stanowią dzienne notowania sześciu towarów z grupy *soft commodities*: kawy, kakao, cukru, bawełny, kauczuku i mrożonego koncentratu soku pomarańczowego, w okresie od 2010 do 2018 roku. Ich celem jest ocena efektywności zastosowania wybranych wskaźników i oscylatorów opartych na średnich ruchomych o różnej długości. Otrzymane wyniki pokazują, że w badanym okresie najbardziej efektywne było wykorzystanie pięciodniowych prostych i ważonych średnich ruchomych oraz oscylatora Momentum, przynosząc pozytywne rezultaty na pięciu z sześciu analizowanych rynków *soft commodities*.

Słowa kluczowe: *soft commodities*, analiza techniczna, efektywność reguł analizy technicznej