Cross-Sectional approach in a trend-follower strategy: momentum within and across asset classes

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Executive Summary

Until now, a wide range of research was concerned with the efficiency of the markets and a lot of them concluded that they are not that efficient. The industry though does not need an evidence for that because they already know. One of the area of strategies that are used by commodity trading advisors is called trend-following. The basic approach is to analyse past price data from an instrument, to judge the trend and therefore to probability of a future price movement. The overall approach then also profits from the flexibility to go long or short and diversify over a broad universe of underlyings. Now it would be interesting whether this method could be improved by considering the past prices of *other* instruments that might influence the price of interest.

As for doing this, the idea is to use statistical methods to filter out first order dependencies between different instruments. Despite a lot of methods were discussed, the most practicable was a stepwise multiple regression. The regression was then used to select the combined most significant instruments, which could be used to replicate the target instrument one time step earlier. This was done on daily prices from over 40 futures time series covering more than 18 years of in- and out-of-sample data. The found factors were then aggregated into an auxiliary series up on which trading signals have been generated. Either simple trend signals from the auxiliary series were used or the information that some regressions did not reach an adequate fit for the given period. This non-fitting periods acted as an indication for possible trend changes or changes in the lead-lag relationship. With the generated signals, it was afterwards tried to enhance a trend-following strategy. Such a trend-follower algorithm was also built on the way to answer the question of possible added value through cross-sectional correlations. The simple algorithm contained the major components: entry, exit, money- and risk management. As for entry and exit signals, a basic but powerful three moving average system has been used.

The signals from the auxiliary series were combined in three ways to check their value with respect to the trend-following algorithm. First, the basic three moving average trend signal was used to add or reduce weight to the given position signal from the trend-follower. Second, bad model fits were additionally used as a position scaling technique because of the assumption that confidence is low during this periods. Third, an independent strategy was built with the auxiliary trend signals and then combined by weighting. Unfortunately, it was then concluded that the added value is rather mediocre for the first two approaches because the reward to risk measures worsened from 1.292 in-sample (0.726 out-of-sample) to 1.147 (0.527) and 1.191 (0.638). Additionally, the drawdown periods got deeper as well. Since the auxiliary trend signals only showed a correlation of 0.584 to the trend-follower, their combination led to an overall improved result. Reward to risks of 1.231 (0.737) and drawdowns of 16.53% (21.55%) were achieved with a light tailed returns distribution. Despite quite well results, the practical implementability is rather limited, nonetheless, is has been shown that by using the right methods, cross-sectional correlation is able to add value to a basic trend-follower.

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List of Abbreviations

$\bar{R}^2$ .... Adjusted coefficient of determination
β .... Regression coefficient
χ^2 .... Chi-squared distribution (cumulative)
δ .... Convenience yield/benefit
$\mathbb{E}[\,]$ .... Expectation
∇ .... First-order differencing
ν .... Trend term
σ .... Real standard deviation
σ^2 .... Real variance
$\tilde{r}$ .... Estimated autocorrelation coefficient
$\tilde{z}$ .... Residual series
$ann.$ .... Annualized (with 250 days)
AuM .... Asset under management
$bn.$ .... Billion
$bu.$ .... Bushel (US)
c .... Cost of carry
$CBOT$ .... Chicago Board of Trade
CCF .... Cross-correlation function
$CFTC$ .... U.S. Commodity futures trading commission
CME .... Chicago Mercantile Exchange
$COMEX$ .... New York Commodities Exchange
CTA .... Commodity Trading Advisor
$Eurex$ .... European Exchange
$Euronext$ .... European Electronic Stock Exchange
F .... F-distribution (cumulative)
FX .... Foreign exchange
HKG .... Hong Kong Futures Exchange
ICE .... Intercontinental Exchange
J .... Number of independent variables
k .... Number of lags
$Liffe$ .... London International Financial Futures and Options Exchange
$m.$ .... Million
N .... Total number of instruments
n .... Index of instruments
$N(\,)$ .... Normal distribution (cumulative)
$NYBOT$ .... New York Board of Trade
$NYMEX$ .... New York Mercantile Exchange
OSE .... Osaka Securities Exchange
r .... Interest rate
R^2 .... Coefficient of determination
s .... Sample standard deviation
t .... Time index
u .... Storage costs
Z .... Noise term

1 Introduction

One method is widely used in the industry and discussed with diverging opinions from time to time. In some points, academics does not agree with practice because most likely not enough variables are known to prove things scientifically. There could also be other reasons but this will not be the main focus thereafter. The saying is primarily of trend-following as well as serial correlations. In the industry, this methods have been already used for a long time, mostly under the name managed futures. They further worked quite well in contrast to most hedge funds strategies.

The subordinated objective of the paper is to examine the mentioned trend-following in a first step. The main target though will be to discuss and evaluate the value of cross-sectional dependencies, which might give the possibility to capture some spillover effects earlier than just by conventional methods. For doing this, trends and basic market characteristics will be discussed at first. Some fundamentals of futures, trends and common strategies are discussed for this purpose as well. The used data, which spans over 47 futures time series from 1970 up to 2012 will be statistically evaluated in a next step. This is then complemented by possible statistical procedures, that are able to filter out the demanded dependencies. The focus will lay on the widely known time series analysis methods because they already are quite powerful to deal with first order dependencies. Thereafter a basic trend-following algorithm is designed whereas to focus is given to simplicity and stability. In a last step, the most promising statistical method will be implemented and processed such that some useful trading signals can be generated. Because the whole procedure should not only be tested for theoretical implementation, some intention is given to practical consideration with regards to implementability. The statistical methods should try to capture those cross-sectional dependencies from nearby futures contracts, if there are any, and then try to forecast basic behaviour of the target instrument. This means, that one tries to predict some components of the movement of one time series by the already available, past price information from other series as well as from its own past. It is then evaluated whether such past information is able to predict some of the futures price movements of a given time series. The astute reader already knows, that this directly affects some of the efficient market hypotheses.

To summarize, three major hypotheses should be examined through the course of this paper. At a first step it should be answered whether there is sustainable return in trend-following like the industry is doing it widely. Mathematically speaking, is there positive serial-correlation and how can it be exploited? Chapter 4 primarily address this question. Thereafter during chapter 5, evidence of cross-correlation should be examined and if found, processed to generate and test trading signals. Finally in the concluding chapter, positive findings should be combined and tested on the hypothesis whether cross-sectional signals carry other useful information than the already included evidence from own price history.

2 Theoretical introduction

In theory there has always been a lot of discussion about the reason why different possibilities to gather returns were present in the markets. Most of them are a compensation for bearing risk, which is referred to the so called risk-premium. But it is also common knowledge that markets are neither throughout rational nor always efficient. To describe that irrationality the topic of behavioural finance was introduced. The interaction of such market dynamics give way to some return opportunities since at least someone has to be there to bring markets back to equilibrium. Therefore, the following sections provide a short introduction of major methods to detect and capitalize on inefficiencies as well as a basic brush up on fundamental concepts of futures. Special weight is given to trends and corresponding models with link to industrial usage. The assumption behind those techniques is that as long as there are some not fully rational market participants, opportunities to profit from them exist.

2.1 Futures contracts

Those instruments are running under the umbrella term of derivatives. Because their payoff is characterized by a linear function, they are one of the more basic one's under the section of derivatives. Futures contracts are, in contrast to forwards, standardized by the exchange that originates them. For each contract there has to be specified which asset the contract is referred to, how much the size of one contract is as well as where, when and which quality has to be delivered. More details about these specifications can be found in the work of Hull (2009). Because the primary focus referred to implementing the examined strategies lies on Commodity Trading Advisors (CTA), which have access to a lot of capital, highly liquid instruments have to be used. One category of instruments that fulfils the liquidity criteria are futures contracts, although they are not only therefore widely used in practice. To elaborate on what liquidity means in this case, one could take a look at the average turnover in the corn contract. A daily turnover of one hundred thousand contracts is normal, which is equal to a nominal of 500 m.bu. or with a price of 722 cent per bu. around 3.61 bn.$. However, since there are some differences in liquidity between the underlyings, the biggest CTA's have to consider that in advance. Further, futures also provide access to one of the oldest contracts, commodity futures. Initially established and used in Japan in the 17th century, when samurais were paid in rice and the primary objective was to hedge their (rice)-income. Nowadays, according to Frankfurter and Accomazzo (2010) the major function was and still is hedging. Behavioural characteristics of hedging due to macroeconomic factors was examined by Khan et al. (2008).

Another valuable characteristic of futures contracts is the diversification potential, which follows out of the wide universe of investable underlyings. Due to the low correlation among sectors and even within sectors, a basket of highly volatile futures carries on average much less risk. Even with a long-only portfolio, which