Absolute Alpha with Moving Averages: a Consistent Trading Strategy

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Abstract

In this paper, we introduce a trading strategy assuming price action to be a martingale. Borrowing the philosophy from short- and long-run reversal strategy, we quantify specific entry points for traders to act on. Such strategy allows traders to allocate risk on benchmark in a reasonable manner.

1 Introduction

Carhart (1995, 1997) discussed a 4-factor model using Fama and French's (1993) 3-factor model plus an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly. The model can be interpreted as a performance attribution model, where the coefficients and premia on the factor-mimicking portfolios indicate the proportion of mean return attributable to four elementary strategies: high versus low beta stocks, and one-year return momentum versus contrarian stocks. In his algorithm, the factor is composed by taking the difference of stocks went up the most and stocks went down the most and it treats all cross sectional stocks the same. Such argument ignores different dynamics among stocks and directly makes investment decisions by return of price on stocks across sections.

De Bondt and Thaler (1984), provided empirical evidence to show that the overreaction hypothesis is consistent in market level. That is, they have shown that portfolios of prior "losers" are found to outperform prior "winners". We take De Bondt and Thaler (1984) as a major assumption for our paper. We assume the existence of short- and long-run reversals. Under this assumption, we arise the question to seek a consistent and quantifiable entry for a particular stock. If short- and long-run reversals do exist, what would be an ideal entry?

Another giant, Burton Malkiel, presented an idea that stock prices follow random walk. We take his words as another underlying assumption in our paper. The stock price is a martingale event. The action of stock price, the probability in the future, cannot be predicted by the probability in the fast. For any stock, the price of the stock at time t, P_t, is independent of the price of the stock at time $t+1$, P_{t+1}. In other words, the probability for stock price to go up at time t, P_t^u, is the same as the probability for stock price to go down at time $t+1$, P_{t+1}^d, following Brownian Motion.

The Section (2) will discuss the mathematical model to quantify entry points in stocks. In Section (3), the paper presents some empirical results. In Section (4), we discuss our interpretation why our model does not disobey EMH. In Section (5), we finish the paper with a final conclusion and open up some potential questions for future research opportunities.

2 Model

2.1 Moving Averages

Yin (Feb., 2016) discussed a model generating alpha by directly investing the market with a weight (a leverage) calculated by the difference between price and moving averages. For a given benchmark, the price of the benchmark i at a time t is $P_{i,t}$ and we can calculate its simple moving average over n days by the following form

$$SMA(i,t)_n = \frac{1}{n}\sum_{j=1}^{n} P(i,t)_j \tag{1}$$

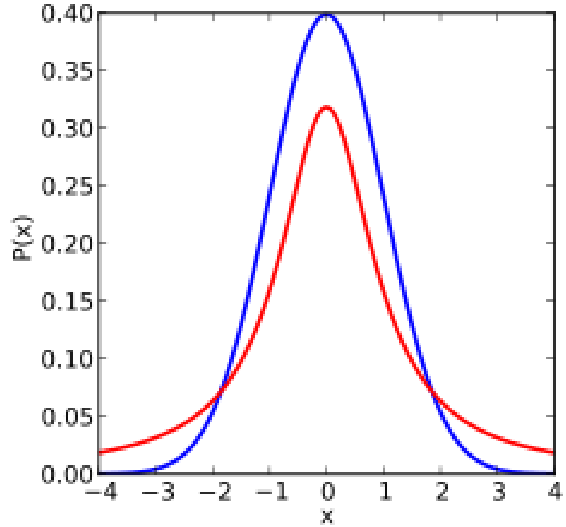
Given price of a benchmark and calculated simple moving averages, $SMA(i,t)_n$, we can calculate exponential moving averages by the following form

$$EMA(i,t)_n = P_{i,t}\theta + \frac{1}{n}\sum_{j=1}^{n} P(i,t)_j(1-\theta) \tag{2}$$

with the weight $\theta = 1/(n+1)$. The simple moving averages calculate average prices directly taking the mean of n days while the exponential moving averages calculate the weighted average between price and simple moving averages. The exponential moving averages will be less noisy than simple moving averages. Both moving averages will be less noisy while n gets larger since the calculation lags more time into the past.

Malkiel (2005) discussed that the price follows random walk. We take this as our major assumption. We assume that the probability for the price of a benchmark to go up at a time t, $P^u_{i,t}$, is the same as the probability for the price of a benchmark to go down at time $t+1$, $P^u_{i,t+1}$. The price, following a random walk, will move up or down like Brownian Motion. There will be more population in the middle, with smaller probability for up and down, then on both sides, with bigger probability for up and down. If price behaves this way, then moving averages behave the same way disregard which type of moving average we use, simple or exponential. However, we can treat a particular moving average as a series of "fixed" numbers and the price of the benchmark to be a martingale around this moving average.

Figure 1. For any price, x, we can calculate moving averages with less noise. For probabilities of price, $p(x)$, there are more observation in the middle then on the tails. Both price and moving averages exhibit the same pattern, but moving averages will occur with bigger population in the middle than that of price.



2.2 Short- and Long-run Reversals

De Bondt and Thaler (1984) provided empirical evidence for short- and long-run reversals. From Figure 2 and Figure 3 by De Bondt and Thaler (1984)[1], we observe that the loser portfolios outperform the winner portfolios in both 1-36 months time period and 1-60 months period.

[1]Figures are taken from De Bondt and Thaler (1984)

Figure 2. Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1-36) months into the test period.

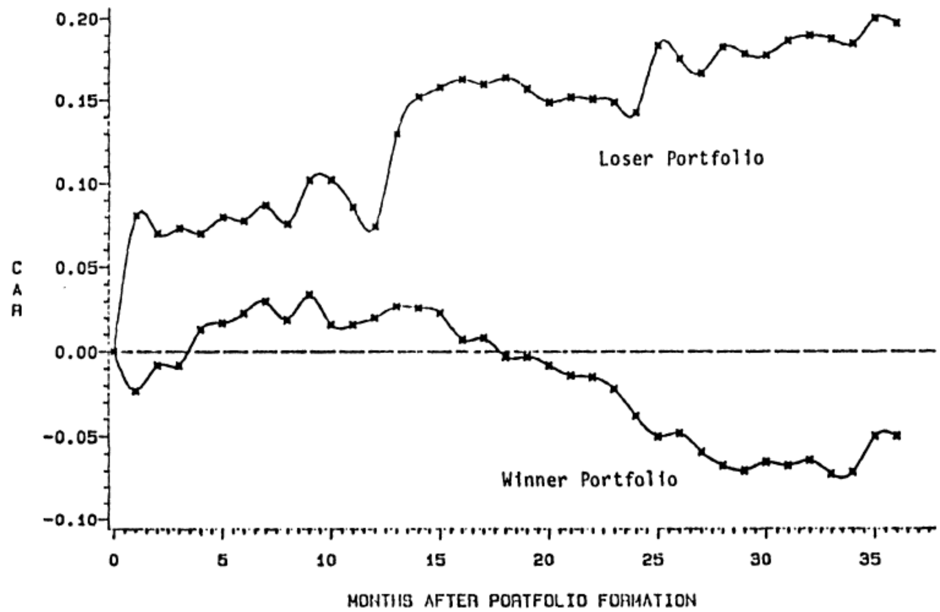
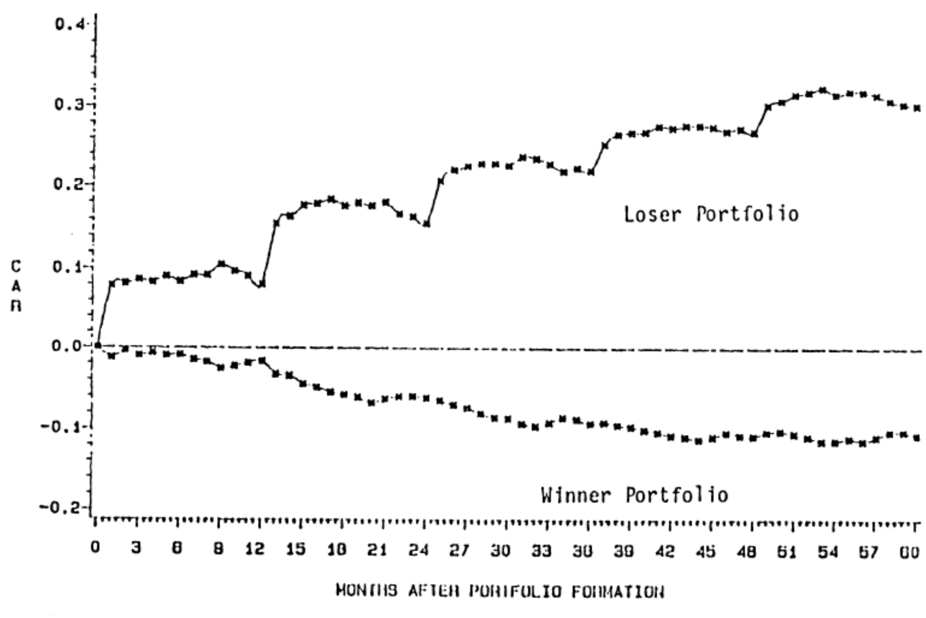


Figure 3. Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1-60) months into the test period.



2.3 Trading Strategy

Under the assumption that price acts like a martingale and the existence of short- and long-run reversals, the goal will be to quantify an entry point consistent to buy a "dip" a trader's risk tolerance allows. To do so, we use moving average to create upper and lower bound on prices with parameters, $\bar{k}$ and $\underline{k}$, respectively.

We denote the upper bound of the price of a benchmark, $\lceil P_{i,t} \rceil$, and the lower bound of the price of a benchmark, $\lfloor P_{i,t} \rfloor$, to be the following forms

$$\lceil P_{i,t} \rceil = \bar{k} \times SMA(i,t)_n = \bar{k} \times \frac{1}{n} \sum_{j=1}^{n} P(i,t)_j \tag{3}$$

$$\lfloor P_{i,t} \rfloor = \underline{k} \times SMA(i,t)_n = \underline{k} \times \frac{1}{n} \sum_{j=1}^{n} P(i,t)_j \tag{4}$$

We can also use exponential moving averages by taking the weighted average between price and simple moving averages. Then the upper bound and lower bound take the following form

$$\lceil P_{i,t} \rceil = \bar{k} \times EMA(i,t)_n = \bar{k} P_{i,t} \theta + \frac{\bar{k}}{n} \sum_{j=1}^{n} P(i,t)_j (1-\theta) \tag{5}$$

$$\lfloor P_{i,t} \rfloor = \underline{k} \times EMA(i,t)_n = \underline{k} P_{i,t} \theta + \frac{\underline{k}}{n} \sum_{j=1}^{n} P(i,t)_j (1-\theta) \tag{6}$$

For each trader, there exists a pair of parameters, $(\bar{k}, \underline{k})$, such that the trader is comfortable with. Given a pair of parameters preferred by a trader, $(\bar{k}^*, \underline{k}^*)$, we can calculate exit price and entry price (buy low sell high) for an ideal position by simple moving average and exponential moving average, respectively,

$$\lceil P^*_{i,t} \rceil = \bar{k}^* \times \frac{P_{i,t}}{SMA(i,t)_n} \tag{7}$$

$$\lceil P^*_{i,t} \rceil = \bar{k}^* \times \frac{P_{i,t}}{EMA(i,t)_n} \tag{8}$$

$$\lfloor P^*_{i,t} \rfloor = \underline{k}^* \times \frac{P_{i,t}}{SMA(i,t)_n} \tag{9}$$

$$\lfloor P^*_{i,t} \rfloor = \underline{k}^* \times \frac{P_{i,t}}{EMA(i,t)_n} \tag{10}$$

with simple moving average to be less noisy than exponential moving average.

3 Empirical Results

We use basic data, market price, for this empirical analysis. We took S&P 500 ETF SPY from Jan. 3rd, 2000 to Mar. 29th, 2016. We run the model with only past data. For example, after the first week, we only have five sample prices to compute standard deviation and there will not be any moving averages calculated with observations more than five. From the period Jan. 3, 2000 to Mar. 29, 2016, we have 4,084 observations of prices for benchmark and we chose moving averages, 10, 20, 30, 50, 100, 200, and 300 as sample moving averages.

We compute simple moving averages based on days described above. In this test, we chose a parameter of $\underline{\mathbf{k}} = \{\underline{k}_{SMA(i)} : i = [10, 20, 30, 50, 100, 200, 300]\}$ to be "buy" signal (as shown in Table 1). That is, given 4,084 trading days from Jan. 3rd, 2000 to Mar. 29th, 2016, this trader would love to trade only 1% of the time, i.e. his "buy" frequency is roughly 0.01. In practice, he may have such goals because of trading cost, patience, risk tolerance, and so on. However, this parameter can be changed to fulfill trader's requirements.

Table 1. The table presents all simple moving averages and parameters $\underline{k}_{SMA(i)}$ such that the "buy" frequency is 1%.

Item	SMA_{10}	SMA_{20}	SMA_{30}	SMA_{50}	SMA_{100}	SMA_{200}	SMA_{300}
$k \times STD$	-0.0726	-0.1094	-0.1025	-0.1417	-0.1707	-0.3725	-0.5307
STD	0.0189	0.0267	0.0331	0.0417	0.0589	0.0891	0.1106
$\underline{k}$	-3.85	-4.1	-3.1	-3.4	-3.75	-4.18	-4.8
Buy Freq.	0.010	0.010	0.010	0.010	0.010	0.010	0.010

Figures 4-10 plot the price of the benchmark, S&P 500 ETF SPY, and the "buy" signals if a price is below lower bound. In other words, under the parameter of $\underline{k} = 0.01$, a trader is able to observe 1% of the trading days during this period such that the closing prices are below lower bound. These are the actionable prices during this period and are on the tails of a normal distribution. A trader should take advantage of this price for as heavy as he could tolerate.

Figure 4. Plot of Price and "Buy" signal when $\underline{k}$ is chosen to be -3.85 using SMA_{10}

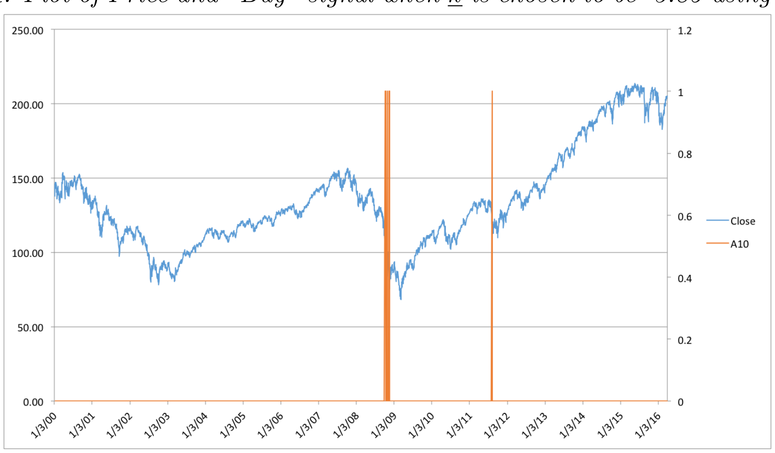


Figure 5. Plot of Price and "Buy" signal when $\underline{k}$ is chosen to be -4.1 using SMA_{20}

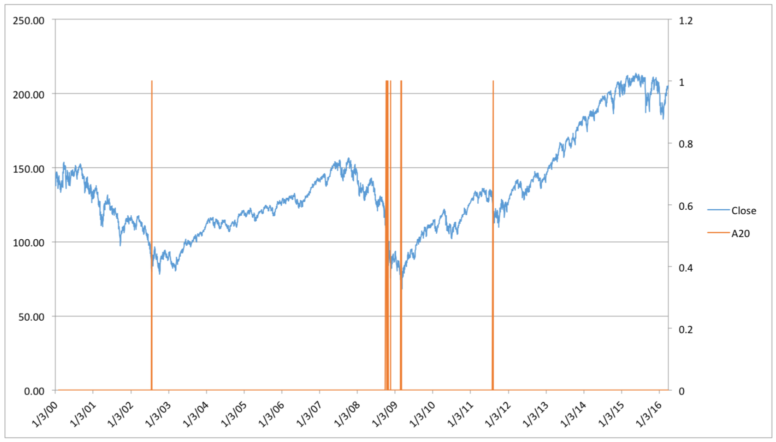


Figure 6. Plot of Price and "Buy" signal when k is chosen to be -3.1 using SMA_{30}

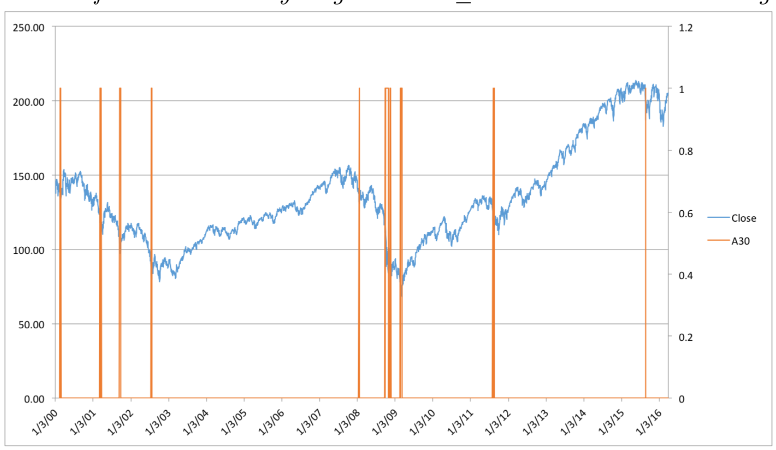


Figure 7. Plot of Price and "Buy" signal when k is chosen to be -3.4 using SMA_{50}

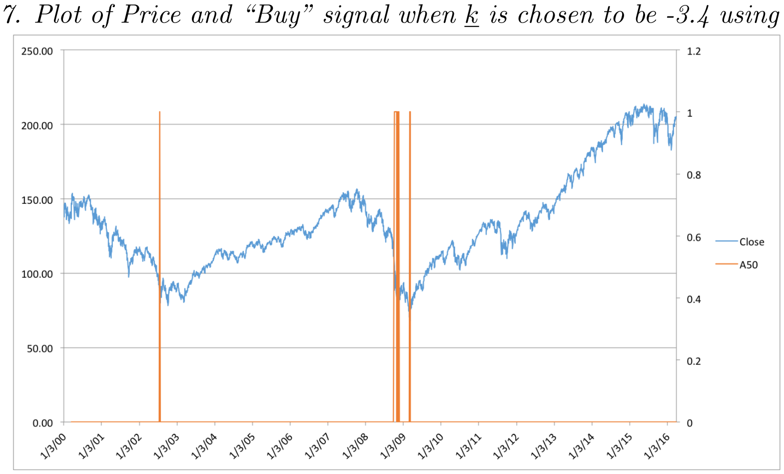


Figure 8. Plot of Price and "Buy" signal when $\underline{k}$ is chosen to be -3.75 using SMA_{100}

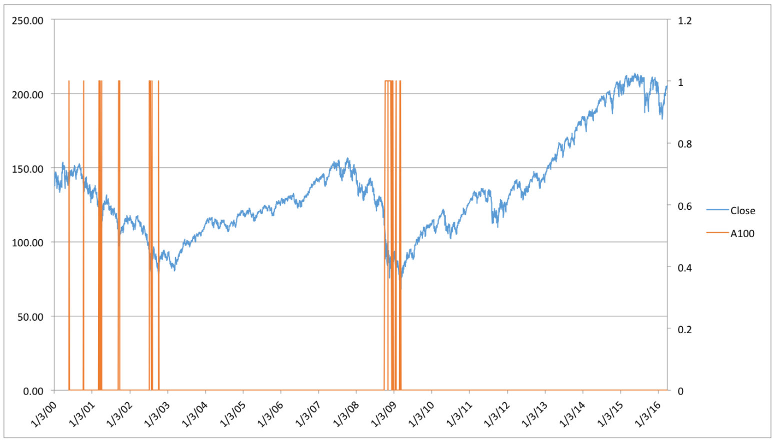


Figure 9. Plot of Price and "Buy" signal when $\underline{k}$ is chosen to be -4.18 using SMA_{200}

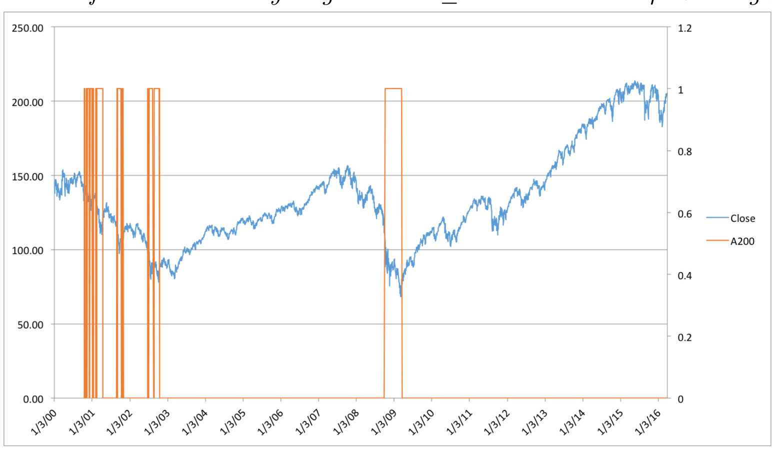
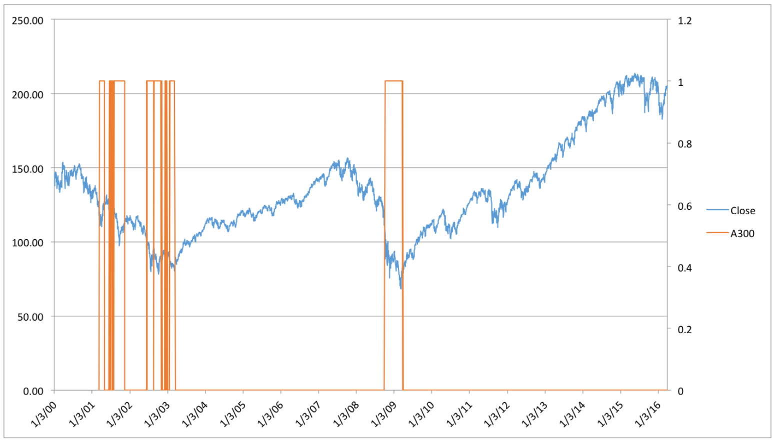
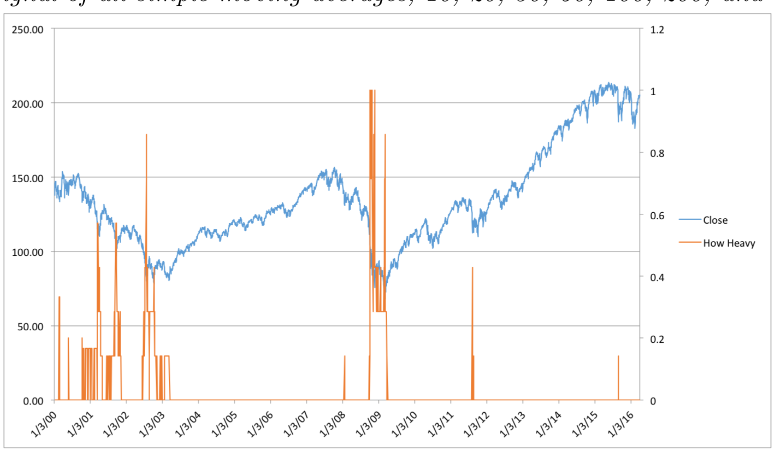


Figure 10. Plot of Price and "Buy" signal when $\underline{k}$ is chosen to be -4.8 using SMA_{300}



One simple moving average may or may not be precise. We can also calculate a the average "buy" signal from all of the moving averages. Figure 11 plots the price of the benchmark and the average of "buy" signal if the average of "buy" signal is bigger than 50%. In other words, the more simple moving averages signal traders to buy the heavier he should buy. The plot only plots the average of "buy" signal if the average of "buy" signal is higher than 3.5 (= 7/2, i.e. 7 moving averages in total, for 10, 20, 30, 50, 100, 200, 300).

Figure 11. Plot of Price and "Buy" signal when k is chosen to be 0.01 using average "Buy" signal of all simple moving averages, 10, 20, 30, 50, 100, 200, and 300



4 Discussion of EMH

This paper introduces a model to take advantage of the volatilities in a benchmark and to outperform a benchmark by consistently allocating risk at probabilistically unlikely pricing events. However, this paper is not meant to attack the Efficient Market Hypothesis. As a matter of fact, the belief of EMH exhibits no effect on this trading strategy.

Efficient Market Hypothesis, as a lot of literature provided empirical evidence, is not a proved theory. Instead it is a belief. As long as a trader is able to minimize greed and fear, a belief should not matter in trading algorithm. On the other hand, this paper does not states price is inefficient in this trading strategy. It is indifferent whether price is correct or not. Whether a trader agrees with market price or not, he should act with consistency in whatever stock screening process he uses. Under a certain parameter based on how often the trader wants to trade, disregard what the reasons are and how rational the reasons are, the strategy introduced in this paper argues a trader should always be consistent following a probabilistically less-likely-happen entry or exit point

Yin (Feb. 2016) explained that such strategy by investing in a benchmark with different weights at different time would be limited to a certain leverage as much as the market allows. That is, at a certain price, there are only so many shares sold and bought. If a buyer is large enough to move the market, then there will be a time in the future when he meets a liquidity problem. This means he will not always be able to achieve a certain amount of leverage he desires to maintain his portfolio growth. For a trader with an arbitrary assets under management, it is easy for him to turn $1 million to $2 million but it will be a lot more difficult for him to turn $1 billion to $2 billion dollars.

This problem, as illustrated in Yin (Feb. 2016), also becomes more and more apparent as time goes by. If a trader is truly an anomaly in the market, he will have some kind of strategy to grow his assets consistently. Eventually there will be one day that he acquires all of the stocks available at that price he desires yet still not big enough for him to grow his assets at a rate he could have done with less assets.

Following this reasoning, a trader trading a strategy with the one introduced in this paper will eventually become a trader with large assets under management and will be facing liquidity problems. He will then be forced to find other stocks under the same strategy. If he infinitely repeats this strategy for all available opportunities out there, he will be exhibiting a similar trading style as short- and long-run reversals. Taking assets under management to infinity, this strategy is consistent with LLR and momentum strategy.

However, U.S. equity market has about $17 trillion market capital. It is not likely a trader could grow big enough to match this size in his life time. Eventually, we, the good ones among us together, are managing the market, but before one of us get to a size that is comparable to all the good ones among us, there is a lot of profitable opportunities for one to exploit.

5 Conclusion

This paper introduces a trading strategy such that a trader can beat the benchmark by directly investing the benchmark with a weight allocated by difference of price and moving averages under the martingale assumption. The algorithm quantifies the exact entry and exit points for a trader based on his parameter's choice. Instead of starting from pure scratch to build a new portfolio, a trader should directly buy the market with a risk profile allocated based on small-probability-price-event.

The paper also opens up a range of new research topics. For example, after a trader enter a position, what percentage of position should he sell when the algorithm tells him it is an ideal exit point? What sort of game plan should he execute to achieve the maximum payoff? To answer these questions, one might want to consider psychological behavior such as Fibonacci number series.

Another question that deserves attention is the maximum leverage a trader is able to take at each time the algorithm signals him to buy. Will strictly following the algorithm gives him optimal psychological behavior in a volatile trading environment? If not, how much will this effect influence his trading behavior and decision making process? And how does it affect his final payoff?

References

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