Analysis Swing Trading Strategy and Compare to Passive Holding

Summary

Swing Trading is a short-term trading method that can be used when trading stocks and ETFs which positions can be days to several weeks. The main goal of swing trading is to identify the trend, capture gains and avoid the loss. In this analysis, our team has constructed two sets of moving average indexes to identify trend while assign trading directions at the same time.

Our team has compared two pairs of indexes in order to make one optimal swing strategy based on different macroeconomics, hence bullish and bearish markets. Then we have compared to the alternative strategy which is holding passively. The reason why investors should follow our swing strategy is that the intuition of our strategy is trying to avoid big loss during economics crisis and small loss during an retrace in the uptrend by actively trading guided by our indexes.

Our strategy can deliver an alpha when there is a bullish market and our assumption is based on no-arbitrage theory. In our analysis, our alpha is mainly delivered by compensation of RMW and Mkt-rf risks during Bullish market. The intuition behind this risk is that while we are trying to avoid small loss during an retrace in the uptrend, we would also ignore small returns after retracing. Moreover, in our assumptions, we have also assumed that there is no transaction cost which commission fee in the ETF market is, and it can be huge due to actively trading behavior.

Bearish Daily Return	-0.02652	Bearish Daily SD	0.30075	Bearish Daily SR	-0.08817
Bullish Daily Return	0.00235	Bullish Daily SD	0.01399	Bullish Daily SR	0.16811

(Expected excess return, volatility, and Sharpe ratio of Swing Trading Strategy)

Link of Uploaded video:

1, Introduction of swing trading analysis

1a, Introduction of swing trading strategy.

Trends of stocks or ETFs are rarely move in a straight line, but instead in a zig-zag pattern. An ETF could go up by a period of time, followed by a smaller backdown for a shorter time and then heading up again. If several of these zig-zag patterns are connected, and the price line appears to be moving higher in some kind of certainty, the ETF can be determined in an uptrend. Likewise, downtrends also tend to move in a step-like figure. An ETF could decline for a relatively longer period of time and then it would correct part of the loss in the next few days by increase a shorter period of time and decrease again. When this phenomenon is repeated, the downward trend is appeared. By trying to identify the beginning point of a steady uptrend and the bottom of a retrace point in a bearish market, we believe swing trading can establish an abnormal return.

1b, Different swing trading strategies.

For identify the direction of trend, we have set two moving average indexes whereas the shorter moving average index surpass the longer index indicates that the growth is abnormally stronger than the past long period of time represents as uptrend. Likewise, when the shorter term of average sinks below the longer one means a weaker short-term trend which is a downtrend. But how to set the two different moving average indexes?

First, we have a pair of shorter periods moving average indexes which are 10-days moving average and 30-days moving average which 10-days on top of the 30-days indicates a buy signal on the uptrend. We then construct another pair of longer period average which are 50-days and 200-days which 50-days on top of the 200-days indicates a buy signal on the uptrend. The 10-30 days sets, 50-200 days sets are two pair of indexes that are used the most frequently in real swing trading brokers and platforms. So, what is the difference between two different trading strategies? In other word what are the pros and cons of them? Due to the nature of swing trading which is insensitive of small loss, there is a lagging of reorganization of buy and sell position which could cause more gain or loses in a different situation. The longer the indexes, the smaller of a day gain or loss effect on it, therefore 10-30 indexes are more sensitive than 50-200 indexes, but they can be both benefit in different situation.

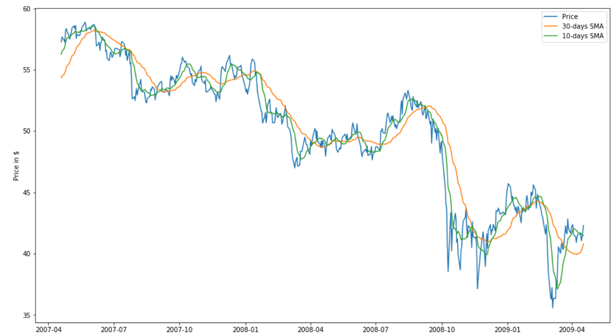
1c, Data set and different testing periods.

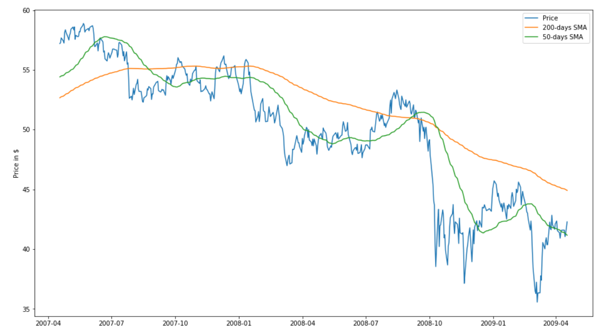
We have decided to choose United States industry ETFs from iShares by BlackRock, Inc. since it is the largest ETF trading corporation by market share for our dataset. We then avoid part of selection bias by randomly choose daily price of 7 different ETFs and they are IHE (U.S. Pharmaceuticals), IEZ (U.S. Oil Equipment & Services), ITB (U.S. Home Construction), IBB (Nasdaq Biotechnology), IHI (U.S. Medical Devices), IGV (North American Tech-Software), ITA (U.S. Aerospace & Defense), with 10 years annual average return range from -2.50%(IEZ) to 17.01%(ITA). By testing the pros and cons with two different pairs of moving average indexes, we have also selected two data periods and they are '2007-04-19' to '2009-04-19' which represents the downtrend due to the 2008 economic crisis; '2016-09-28' to '2018-09-28' which represents a relatively robust uptrend economy.

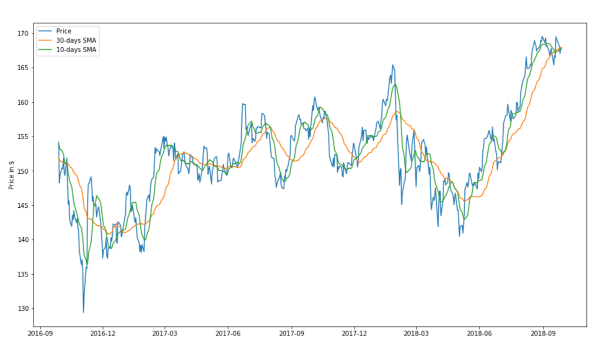
2, Test Procedure

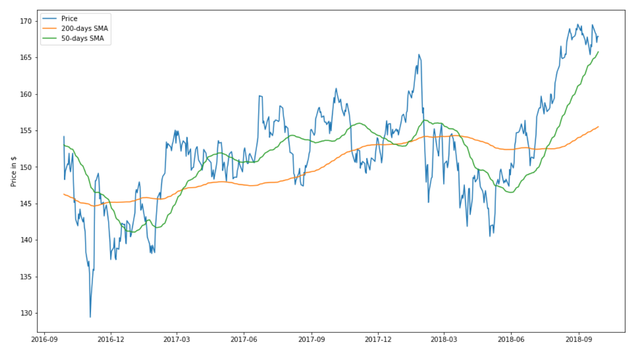
We first have chosen different period data set in order to make two pairs of indexes start and finish in the same day and then calculate the moving average of 10, 30, 50, 200 days of each ETFs by rolling and plot them with price.

```
# plot 10 days and 30 days moving average
start_date = '2007-04-19'
end_date = '2009-04-19'

fig, ax = plt.subplots(figsize=(16,9))

ax.plot(price.loc[start_date:end_date, :].index, price.loc[start_date:end_date, 'IHE'], label='Price')
ax.plot(rolling30.loc[start_date:end_date, :].index, rolling30.loc[start_date:end_date, 'IHE'], label = '30-days SMA')
ax.plot(rolling10.loc[start_date:end_date, :].index, rolling10.loc[start_date:end_date, 'IHE'], label = '10-days SMA')

ax.legend(loc='best')
ax.set_ylabel('Price in $')
```









(Example: IHE)

We can clearly see that the 07 to 09 period is in downward trend whereas 16-18 is an upward trend. We also find that 10-days and 30-days moving average is more sensitive to price in term of more frequent intersections than 50-days and 200-days moving average intersections.

We then sign a "buy and hold" signal when 10-days moving average is above 30-days moving average, otherwise sign a "sell and hold" signal when it is below. In other hand, 50-days and 200-days indexes are assigned in the same way. And then we calculate each day's return by $\frac{Price_n - Price_{n-1}}{Price_{n-1}}$ when we are in "buy and hold" position and assign a return of 0 when in "sell".

```
# Decide buy or sell
bs_IHE1 = pd.DataFrame(rolling10.loc[:,'IHE'])
bs_IHE1.rename(columns = {'IHE':'10days'},inplace = True)
bs_IHE1['30days'] = rolling30.loc[:,'IHE']
bs_IHE1['Price']=price.loc[:,'IHE']
bs_IHE1['bs'] = np.nan
IHE1=bs_IHE1.loc['2007-4-18':'2009-4-19',].copy()

for i in IHE1.index:
    if IHE1.loc[i,'10days'] >= IHE1.loc[i,'30days']:
        IHE1.loc[i,'bs'] = 'buy'
    else:
        IHE1.loc[i,'bs'] = 'sell'
```

```
# Calculate return

IHE1['Return']=np.nan

for i in range(1,IHE1.shape[0]):
    if IHE1.iloc[i,3]=='buy' :
        IHE1.iloc[i,4]=(IHE1.iloc[i,2]-IHE1.iloc[i-1,2])/IHE1.iloc[i-1,2]

    if IHE1.iloc[i,3]=='sell':
        IHE1.iloc[i,4]=0
```

(Example: IHE in 10,30-days moving average strategy in '2007-04-19' to '2009-04-19' period)

We have then calculated the total return with different ETFs, strategies indexed and periods.

	IHE	IEZ	ITB	IBB	IHI	IGV	ITA
07-09(10-30)	-4.39%	23.71%	-17.40%	-5.33%	10.82%	6.03%	33.92%
07-09(50-200)	-24.02%	-1.50%	-21.18%	-32.41%	-18.10%	-15.79%	4.78%
16-18(10-30)	-2.63%	-8.78%	34.97%	-6.25%	34.55%	15.20%	41.04%
16-18(50-200)	-9.54%	-26.91%	28.95%	1.53%	41.16%	79.76%	66.23%

As we can see the total return from the above, we have found the optimal trading strategy which is for IHE, IEZ and ITB we decide to use 10-30 as index no matter the trends, but for IBB, IHI, IGV and ITA we decide to use 10- and 30-days moving average from 2007-09 and use 50 and 200 days during good economic period such as 2016 to 2018. Then we have utilized these seven ETFs combine into two tangent portfolios by:

```
Wmve=pd.DataFrame([],index=port1.columns)
Wmve['tangent1'] =np.linalg.inv(Cove1) @ ERe1.values
Wmve['tangent1']=Wmve['tangent1']/Wmve['tangent1'].sum()
Wmve/100
```

```
Wmve2=pd.DataFrame([],index=port2.columns)
Wmve2['tangent2'] =np.linalg.inv(Cove2) @ ERe2.values
Wmve2['tangent2']=Wmve2['tangent2']/Wmve2['tangent2'].sum()
Wmve2
```

	IHE	IEZ	ITB	IBB	IHI	IGV	ITA
Portfolio 1	0.2151	-0.00440	0.0321	0.1554	-0.0764	0.0492	-0.3215
Portfolio 2	-0.5988	-0.2694	0.4377	-0.5808	0.3056	0.6965	1.0092

Then we have calculated expected excess returns, standard deviations and Sharpe ratios of these two portfolios represents in the summary page.

Port1 return	-0.02652	Port1 SD	0.30075	Port1 SR	-0.08817
Port2 return	0.00235	Port2 SD	0.01399	Port2 SR	0.16811

Next, we have made two OLS regression which x are two portfolio daily returns and y are daily 5 Fama-French Factors from '2007-04-19' to '2009-04-19' and '2016-09-28' to '2018-09-28' imported from Kenneth R. French Data Library, and the results are:

Dep. Variable:	y	R-squared:	0.030
Model:	OLS	Adj. R-squared:	0.020
Method:	Least Squares	F-statistic:	3.103
Date:	Sat, 17 Nov 2018	Prob (F-statistic):	0.00907
Time:	17:11:24	Log-Likelihood:	-101.38
No. Observations:	504	AIC:	214.8
Df Residuals:	498	BIC:	240.1
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0213	0.013	-1.593	0.112	-0.048	0.005
SMB	1.5472	1.730	0.894	0.372	-1.852	4.946
HML	-1.7179	1.615	-1.064	0.288	-4.890	1.454
RMW	-10.7472	3.647	-2.947	0.003	-17.912	-3.583
CMA	7.5237	3.623	2.076	0.038	0.405	14.643
Mkt-RF	-0.6759	0.757	-0.893	0.373	-2.164	0.812

Omnibus:	46.202	Durbin-Watson:	2.066
Prob(Omnibus):	0.000	Jarque-Bera (JB):	208.285
Skew:	-0.218	Prob(JB):	5.91e-46
Kurtosis:	6.119	Cond. No.	308.

Dep. Variable:	y	R-squared:	0.415
Model:	OLS	Adj. R-squared:	0.409
Method:	Least Squares	F-statistic:	70.73
Date:	Sat, 17 Nov 2018	Prob (F-statistic):	7.62e-56
Time:	17:11:24	Log-Likelihood:	1572.5
No. Observations:	504	AIC:	-3133.
Df Residuals:	498	BIC:	-3108.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0013	0.000	2.685	0.007	0.000	0.002
SMB	0.1474	0.099	1.493	0.136	-0.047	0.341
HML	-0.0521	0.118	-0.442	0.658	-0.284	0.179
RMW	1.0973	0.150	7.295	0.000	0.802	1.393
CMA	-0.3361	0.182	-1.844	0.066	-0.694	0.022
Mkt-RF	1.3205	0.076	17.440	0.000	1.172	1.469

Omnibus:	5.246	Durbin-Watson:	1.987
Prob(Omnibus):	0.073	Jarque-Bera (JB):	6.547
Skew:	0.082	Prob(JB):	0.0379
Kurtosis:	3.534	Cond. No.	416.

	Alpha	SMB	HML	RMW	CMA	Mkt-rf
Portfolio 1	-0.0213(fail)	1.5472(fail)	-1.7179(fail)	-10.7472(rej)	7.5237(rej)	-0.6759(fail)
Portfolio 2	0.0013(rej)	0.1474(fail)	-0.0521(fail)	1.0973(rej)	-0.3361(fail)	1.3205(rej)

3, Conclusion

We have concluded that swing trading strategy would perform better when they have relatively smaller indexes in bad macroeconomy and larger indexes when market is in a good situation.

For portfolios, in economics crisis which from '2007-04-19' to '2009-04-19', portfolio 1 fail to deliver an alpha under 95% confidence. On the other hand, the portfolio 2 which performs in a relatively good economy from '2016-09-28' to '2018-09-28' has successfully deliver a 0.0013% daily alpha under 95% significance level. In the chart above we also have couple betas survive under 95% significance level. The portfolio 1 will have risk exposure on RMW and CMA which one unit of Robust minus weak will lower 10.7472% of the portfolio 1's return and one unit of Conservative minus Aggressive would result a 7.5237% increase in return. In portfolio 2, RMW and Mkt-rf survive which means one unit of Robust minus weak would cause an increase of 1.0973% in return while one unit of Rm-Rf would boost 1.3205% of return. Above all, we recommend our swing strategy rather than holding the ETFs passively, since it delivers no negative alpha under 95% significance level in economy crisis while deliver positive alpha when the economy is good.