

An Application of ETF Discount and Premium Rate in the Index Timing Strategies

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Abstract: During these years, the development of Chinese financial market leads to various financial products available to investors. Considering the current situation of Chinese financial market, timing strategies could bring abnormal return higher than pure passive investment. The index investment is more preferred due to its low transaction cost and high level of transparency. Exchange-traded fund (ETF) could track the index by an arbitrage mechanism given by purchasing and redeeming units. Although traditional strategies focusing on technical analysis indicators such as moving average lines are widely used among investors, they could possibly mislead investors during fluctuation and offer outdated information. Since ETFs are based on indices, the trading data of ETFs could offer incremental information for index timing above classical technical indicators. Moreover, ETFs could track indices in real time, which allow us to construct trading signals with less lag. In this paper, based on trading data of ETFs and corresponding underlying indices at minute frequency, we construct three timing signals (open-close signal, day-close signal and volume-based signal) and a combined signal. We also conduct back-test for these signals with the most two liquid indices (SSE50 and CSI300) in Chinese market.

1. Introduction

A wide range of financial products occur in Chinese market in few decades. For example, China Asset Management Co. Ltd started to manage the first ETF in China in 2005. In 2014, Shanghai 50 Stock Index Future was set up by China Financial Futures Exchange (CFFEX). One year later, the option with SSE 50 ETF as underlying was allowed to be traded in Chinese market (Jing 2011). On the one hand, these financial products provide various investment tools for the large amount of investors in China. On the other hand, we can also observe investors' sentiment to indices based on changes of these products.

Based on the Capital Asset Pricing Model (CAPM), the return has two resources: alpha and beta, which represent the abnormal return and market fluctuation respectively (Zhang 2017). When using pure passive investment strategies, investors can only obtain profit from beta, which reflects the performance of the market (Dapena 2015). However, different from American market, there are some opportunities to obtain profit from alpha in A-share market due to following reasons. The first reason

is the large proportion of individual investors. Many individual investors will follow to buy a stock after going up and sell it after going down, which is easily stuck with some inferior stocks. Such irrational actions will lead to larger possibility and magnitude of gathering abnormal return. Secondly, the lower transparency makes the market less efficient (Yuan 2017). Thus, there exist alpha profit gained from timing strategy or share selection. This paper aims to describe the market sentiment to indices based on constructing a signal as well as use it in timing strategies in order to obtain abnormal return.

Some technical indicators such as moving average (MA), moving average convergence / divergence (MACD), KDJ index, relative strength index (RSI) are commonly used in timing strategies (Wu 2015). These indicators have two disadvantages. Firstly, all of these indicators are based on moving averaged price. They use prices during a period of time to construct measures and predict the future trend of the market. So, these lagging indicators could mislead investors especially in volatile market (Oriani 2016). Moreover, these indicators based on daily frequency data are calculated by close prices each day, containing a limited number of data. They cannot reflect the trading details during one day hence have limited efficiency. Abnormal return brought by these indicators will disappear gradually with the increase of market efficiency (Manahov 2014).

In this paper, we use trading data on the frequency of minute during a day to construct timing signal, instead of relying on the past data. This method avoids the hysteretic nature and the insufficiency of information compared with traditional methods. The main idea of timing strategy is to construct suitable signal and to judge sentiment to the market by analyzing trading data of both ETFs and indices (Checkley 2017). We do back test on the most two common indices SSE50 and CSI300 to test our strategies. We construct three different signals in different ways. The first one is based on the return in each minute at the beginning and ending of each day which accurately reflect the sentiment to the market. The second one compares the data at the ending and the whole day data to construct signal. The third one uses trading volumes to reflect the market sentiment. In the last signal, we combine all signals above. The result shows that our strategies outperform significantly than the benchmark. For the first signal, the Sharpe ratio for both SSE 50 and CSI 300 are higher than benchmarks, with lower volatility and maximum of drawdown. For the second one, the performance is similar to the first signal on SSE 50 but outperforms sharply on CSI 300. The third signal has the worst performance, almost as same as benchmarks. The last signal has the best performance both in the Sharpe ratio and total return, which means that the factors we consider in this signal actually reflects the market sentiments.

This paper proceeds as follows. In section two, we describe our data with main features and show a sample data form. In section three, we state the methodology. We represent explicitly the calculation processes of each signal and some indicators to measure the performance of each signal. In section four, the results of all signals are shown and compared.

2. Description of Data

In this study, we focus on SSE 50 Index and SSE 300 Index, which are the two most popular indices in China. The corresponding ETFs we use are 50ETF established by China Asset Management Co. and 300ETF established by Huatai-PineBridge Investments Co. These data contain the trading information such as open price, close price, trading volume of these two indices and corresponding ETF each minute as well as the adjusted net asset values of two ETFs, which are gathered from JoinQuant and Tushare financial community respectively. We use data from Jan 2010 to Dec 2019 to construct our strategies. Table 1 and Table 2 show the features of indices and ETFs as a sample data.

Table 1: Trading information of SSE 50 Index each minute.

Time	Code	Open	Close	High	Low	Volume	Money
2005/1/4 9:31:00	000016.XSHG	836.99	832.38	836.99	832.38	5853900	4.88E+11
2005/1/4 9:32:00	000016.XSHG	831.88	829.63	831.88	829.63	3094900	27017490
2005/1/4 9:33:00	000016.XSHG	827.09	827.64	827.64	825.92	4887400	13593718
2005/1/4 9:34:00	000016.XSHG	825.79	825	826.39	824.63	3412800	22509692
2005/1/4 9:35:00	000016.XSHG	825.1	824.71	825.1	824.24	8172700	16093420

Table 2: The adjusted net asset value of 50ETF.

ts_code	ann_date	end_date	adj_nav
510050.SH	20041231	20041230	1
510050.SH	20050104	20041231	0.996
510050.SH	20050108	20050107	0.981
510050.SH	20050115	20050114	0.983
510050.SH	20050122	20050121	0.988

3. Methodology

ETFs track indices by an arbitrage mechanism and keep trading close to their net asset values. ETFs are traded on stock exchanges, so price discount and premium occur occasionally. The price discount means that the price of ETF is lower than the price of corresponding index, which will lead to more bid orders due to the optimistic sentiment. The price premium means that the price of ETF is higher than the price of corresponding index, which will lead to more ask orders due to the pessimistic sentiment. The main idea of timing strategy is to construct suitable signal and to judge sentiment to the market by analyzing trading data of both ETFs and indices. In Chinese stock market, the two most popular indices are SSE 50 Index and CSI 300 Index. SSE 50 Index consists of 50 stocks with highest liquidity and largest scale in Shanghai Stock Exchange, reflecting stock performance of leading enterprises listed in Shanghai. CSI 300 Index consists of 300 stocks with highest liquidity and largest scale in both Shanghai Stock Exchange and Shenzhen Stock Exchange, mainly representing the whole market in China.

3.1. Open-Close Signal

By plotting the averaged trading volumes for each minute in all trading days in Figure 1, it could be obviously observed that the trading is more active during the first 15 minutes and the last 15 minutes than any other time for a day, containing more effective information about market sentiment.

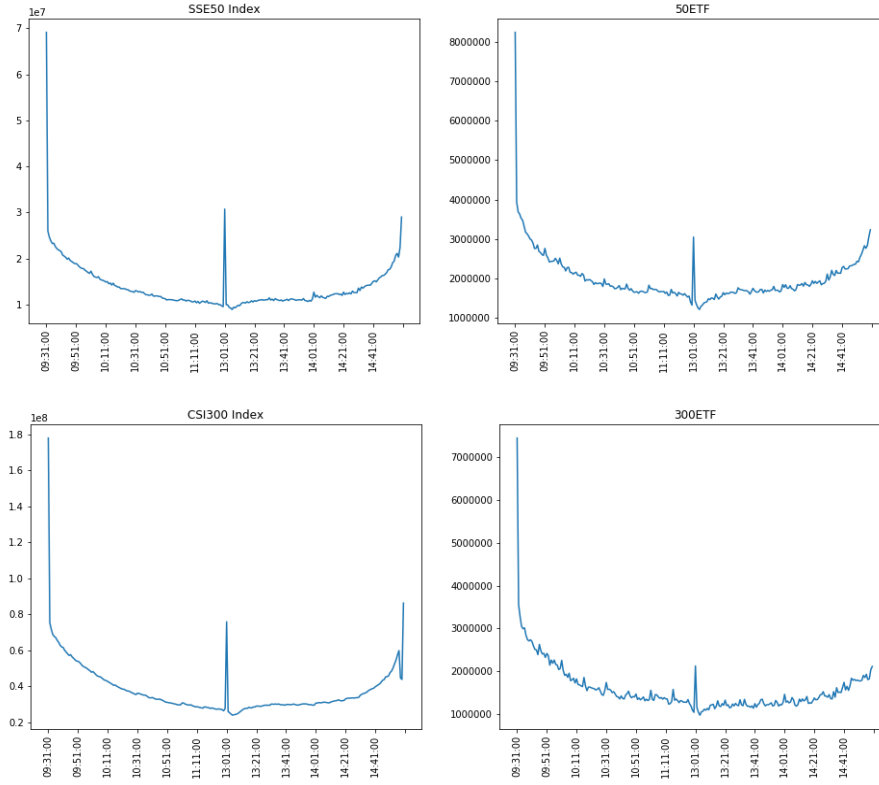


Figure 1: trading volumes for indices and ETFs.

Our main idea is to compare the market sentiment at the beginning and the sentiment at the ending to make a judgement on the changing position. Hence, we extract trading data during these two periods to filter more valuable information. Then, we compare returns of index and corresponding ETF in each minute and calculate the mean of their difference.

$$s_1 = \text{mean}(ret_{index} - ret_{etf}) \text{ in the first 15 minutes} \quad (1)$$

$$s_2 = \text{mean}(ret_{index} - ret_{etf}) \text{ in the last 15 minutes} \quad (2)$$

where ret_{index} is the return of index and ret_{etf} is the return of corresponding ETF.

Then the open-close signal is proposed as

$$signal_1 = I(s_1 < s_2) \quad (3)$$

where $I(x)$ is the indicator function. If the mean value of the first 15 minutes is smaller than that of the last 15 minutes, it means that the number of people longing the ETF is increasing during this day, reflecting a positive sentiment to the market. A negative sentiment could be determined otherwise.

3.2.Day-Close Signal

In the first signal, we only use data in 30 minutes each day, ignoring too much information. In order to use information integrally, we also need to focus on data in the whole day. Similarly, we also

compare the difference between return of indices and ETFs but we use data for the whole day rather than the first 15 minutes, namely,

$$s_1 = \text{mean}(ret_{index} - ret_{etf}) \text{ in the whole day} \quad (4)$$

$$s_2 = \text{mean}(ret_{index} - ret_{etf}) \text{ in the last 15 minutes} \quad (5)$$

Then the signal is equal to

$$signal_2 = I(s_1 < s_2) \quad (6)$$

If the mean value of the whole day is smaller than that of the last 15 minutes, it means that the number of people longing the ETF increases during this day, reflecting a positive sentiment to the market. A negative sentiment could be determined otherwise.

3.3. Volume-Based Signal

In the first two signals, we do not distinguish discount and premium but calculate the mean value instead. So the main idea of this signal is to consider minutes with discount and minutes with premium separately. Firstly, we calculate the difference of return of indices and ETFs. Positive value represents that the ETF is in premium and in discount otherwise. Then we calculate the mean value of trading volumes separately.

$$Vol_{discount} = \frac{\text{sum}(Vol_{i,etf} I(ret_{i,index} > ret_{i,etf}))}{\text{sum}(I(ret_{i,index} > ret_{i,etf}))} \quad (7)$$

$$Vol_{premium} = \frac{\text{sum}(Vol_{i,etf} I(ret_{i,index} < ret_{i,etf}))}{\text{sum}(I(ret_{i,index} < ret_{i,etf}))} \quad (8)$$

where $Vol_{i,etf}$ is trading volumes of ETFs in the i -th minute.

Then the signal is equal to

$$signal_3 = I(Vol_{premium} > Vol_{discount}) \quad (9)$$

The trading volumes when premium is larger represents that the power driving the price to increase is strong, which is a positive signal to the market. Otherwise, if most trading occurs when discount, investors undersell their stocks to close position, reflecting a negative signal to the market.

3.4. Combined Signal

The first signal is constructed based on trading prices in the first and the last 15 minutes. The second one utilizes the price change in the whole and the information about trading volumes is considered in the third one, which are supplements to the first signal. Hence, we combine all of them to build a new signal. Specifically, if more than two signals represent a positive sentiment to the market, it is regarded as a positive sentiment in the combined signal. Otherwise, a negative sentiment is determined. Then, our combined signal is

$$signal_4 = I(signal_1 + signal_2 + signal_3 \geq 1) \quad (10)$$

Then we build a trading strategy based on the above-mentioned four signals. For each day, if we don't have any position, we will long one share of stock if signal is one and hold on our position otherwise due to the limitation of short selling in Chinese market. If we have already had a long position, we close the position if signal is equal to 0 and otherwise hold the position. Each time of trading will cost commission, which is equal to 0.025% of the adjusted net value of the ETF.

4. Results

To back test our strategies, we track the daily net asset value and calculate Sharpe ratio, annualized return, maximum drawdown, turnover rate alpha and beta to measure the performance of a strategy. We also calculate the accuracy rate of each signal to test whether signals match the change direction of ETFs' net value. For each signal, we use data of SSE50 during 2010 to 2019 and data of CSI300 during 2012 to 2019 and corresponding ETFs to back test the performance.

4.1. Open-Close Signal

For the open-close signal, the performance measurements are shown in Table 3. It can be seen that this strategy outperforms both indices based on their total returns and Sharpe ratios. This strategy has a significantly higher annual return than the benchmark with a slightly lower volatility, which means that this signal could lead to a more stable and higher profit. The alpha of strategy on SSE50 is about 4.8% and 5.7% on CSI300, which means that the abnormal profit could be obtained through this strategy. Figure 2 plots and compares the net values of strategies on ETFs and benchmarks, showing that this strategy has a modest increasing trend in a bearish market but cannot follow the index totally in a bullish market. Figure 3 visualizes the change of drawdown of both strategies on ETFs and benchmarks. It can be seen that for SSE50, the benchmark has a much large drawdown during this period except in the extremely bullish market in the first half year of 2015. For, CSI300, though the maximum drawdown of the strategy is not sharply smaller than that of the benchmark, it keeps in a stable level before the crash.

Table3: The performance of open-close signal on SSE50 and CSI300.

	SSE50		CSI300	
	strategy	benchmark	strategy	benchmark
total return	1.12	0.43	1.17	0.76
annual return	0.08	0.04	0.11	0.08
volatility	0.15	0.23	0.16	0.23
Sharpe ratio	0.34	0.03	0.51	0.22
max drawdown	-0.37	-0.44	-0.35	-0.46
information ratio	0.25		0.18	
alpha	0.05		0.06	
beta	0.43		0.47	
win rate	0.65		0.66	
average turnover	0.42		0.43	
average holding days	2.37		2.31	

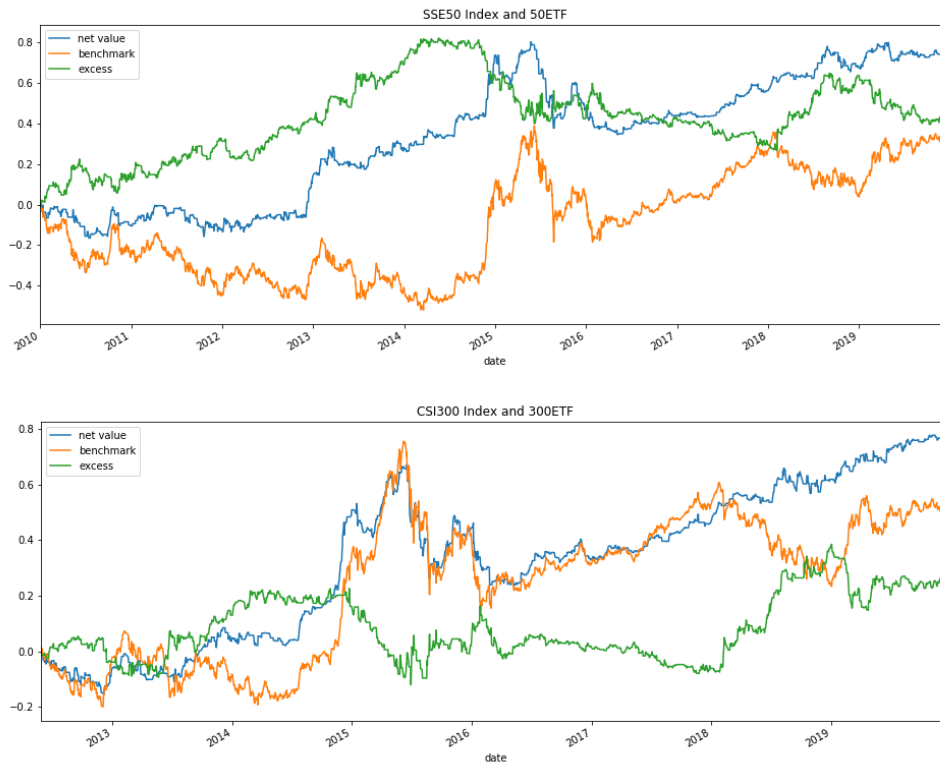


Figure2: Net values of strategies with open-close signal on ETFs and benchmarks.

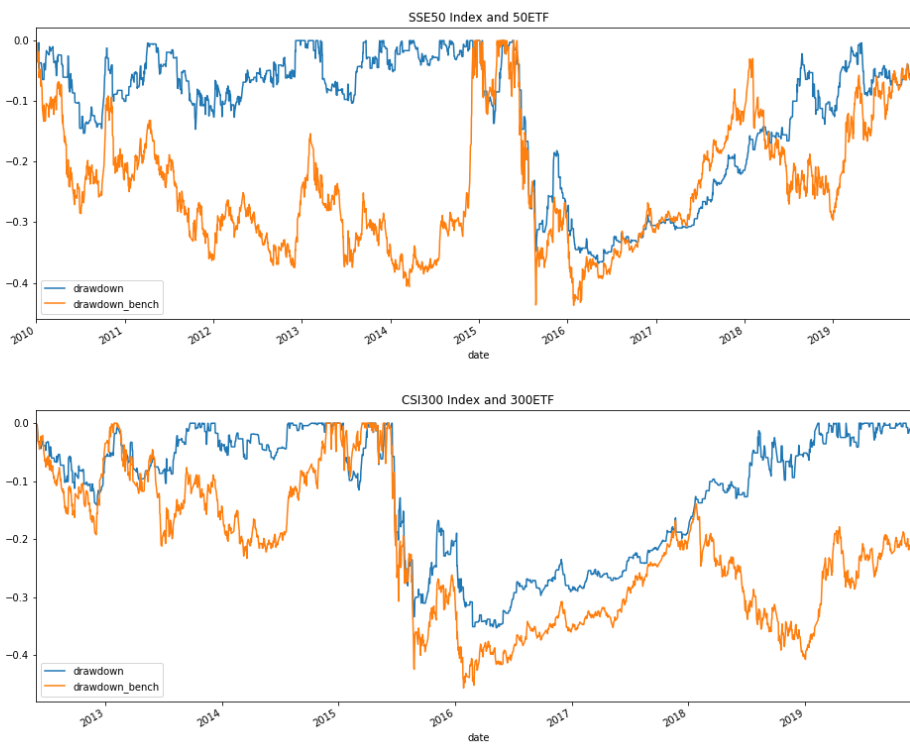


Figure3: Drawdown of open-close signal on SSE50 and CSI300.

4.2. Day-Close Signal

For the day-close signal, the results are shown in Table 4. According to these two tables, we can see that this signal has a similar performance on SSE50 but a much greater performance than open-close signal on CSI300. This signal has around 15% annualized return and 10% alpha, generating a high and stable level of abnormal return. The net value and drawdown curves are shown in Figure 4 in the Appendix. It is shown that the net value of day-close signal strategy increases modestly in both bearish and bullish market, even in the extreme crash during the last half of 2015. In other words, the performance of this signal is less affected by the market, having a smaller beta than open-close signal.

Table 4: The performance of day-close signal on SSE50 and CSI300.

	SSE50		CSI300	
	strategy	benchmark	strategy	benchmark
total return	1.13	0.43	1.92	0.76
annual return	0.08	0.04	0.16	0.08
volatility	0.14	0.23	0.15	0.23
Sharpe ratio	0.36	0.03	0.88	0.22
max drawdown	-0.26	-0.44	-0.20	-0.46
information ratio	0.24		0.43	
alpha	0.05		0.11	
beta	0.38		0.40	
win rate	0.64		0.62	
average turnover	0.46		0.43	
average holding days	2.19		2.35	

4.3. Volume-Based Signal

According to Table 5, the volume-based signal obviously underperforms than the first two signals. The alpha is 1.5% and 2.6% respectively, representing that the abnormal return of this signal is much smaller. Based on the net value and drawdown in Figure 6 and Figure 7 in the Appendix, we can see that the volume-based signal keeps stable in bearish market but cannot follow the benchmark in bullish market and thus, has a similar performance as the benchmarks.

Table 5: The performance of volume-based signal on SSE50 and CSI300.

	SSE50		CSI300	
	strategy	benchmark	strategy	benchmark
total return	0.57	0.43	0.70	0.76
annual return	0.05	0.04	0.08	0.08
volatility	0.14	0.23	0.14	0.23
Sharpe ratio	0.13	0.03	0.32	0.22
max drawdown	-0.32	-0.44	-0.26	-0.46
information ratio	0.06		-0.03	
alpha	0.02		0.03	
beta	0.34		0.36	

win rate	0.64		0.64	
average turnover	0.44		0.44	
average holding days	2.27		2.27	

4.4. Combined Signal

From Table 5, all measurements are improved by combining three signals above. Based on the alpha and the information ratio, the abnormal profit is increased sharply. The slightly decrease in turnover rate represents a lower trading frequency in this strategy, costing less transaction fee. Figure 8 and Figure 9 in the Appendix show that the combined signal could make the strategy benefit from a bullish market but resist the downside of the market, even when a crash occurs. In general, the combined signal outperforms the other three signals.

Table 6: The performance of combined signal on SSE50 and CSI300.

	SSE50		CSI300	
	strategy	benchmark	strategy	benchmark
total return	1.96	0.43	2.06	0.76
annual return	0.12	0.04	0.16	0.08
volatility	0.20	0.23	0.20	0.23
Sharpe ratio	0.45	0.03	0.67	0.22
max drawdown	-0.37	-0.44	-0.33	-0.46
information ratio	0.66		0.76	
alpha	0.08		0.10	
beta	0.72		0.77	
win rate	0.75		0.77	
average turnover	0.38		0.32	
average holding days	2.60		3.13	

5. Conclusions

This paper aims to extract information about the market sentiment to obtain abnormal profit. We construct four signals which are open-close signal, day-close signal, volume signal and combined signal. It could be concluded that the volume signal has the worst performance based on its Sharpe ratio and the magnitude of return. It is mainly caused by the lagging data that we used to construct this signal. The open-close signal and day-close signal have similar performance, and both outperform benchmarks in bearish markets but cannot totally follow benchmarks in bullish markets. The combined signal has the best performance among these signals since it takes both trading volumes and return in each minute into consideration. The information ratio reaches 66% and 76% for SSE50 and CSI300 respectively, much higher than that of other signals. It indicates that this signal could lead to a high level of abnormal profit with a relatively low volatility. In conclusion, this signal could help investors obtain stable and a high level of abnormal return.

References

- [1] Jing W, Zong-Fang Z, Xue-Xi H. Analysis of Tracking Errors Between SSE-50 ETF and SSE-180 ETF Based on SPA[J]. Journal of Northwest A&F University(Social Science Edition), 2011.

- [2] Zhang, Lu. *The Investment CAPM*[J]. *European Financial Management*, 2017, 23(4):545-603.
- [3] José P. Dapena, Siri J R . *Index options realized returns distributions from passive investment strategies*[J]. *Cema Working Papers Serie Documentos De Trabajo*, 2015.
- [4] YUAN Fenqiang, JI Ting, LI Huirong, 等. *Ownership Structure, Information Transparency and Corporate Performance—Based on the Empirical Analysis of Shenzhen A-share Listed Companies*[J]. *review of economy & management*, 2017.
- [5] Wu M , Diao X . *Technical analysis of three stock oscillators testing MACD, RSI and KDJ rules in SH & SZ stock markets*[C]// *2015 4th International Conference on Computer Science and Network Technology (ICCSNT)*. IEEE, 2015.
- [6] Oriani F B , Coelho G P . *Evaluating the impact of technical indicators on stock forecasting*[C]// *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, 2016.
- [7] Manahov V , Hudson R , Gebka B . *Does high frequency trading affect technical analysis and market efficiency? And if so, how?*[J]. *Journal of International Financial Markets, Institutions & Money*, 2014, 28(jan.):131-157.
- [8] M. S , Checkley, D, et al. *The hasty wisdom of the mob: How market sentiment predicts stock market behavior*[J]. *Expert Systems with Applications*, 2017.

Appendix

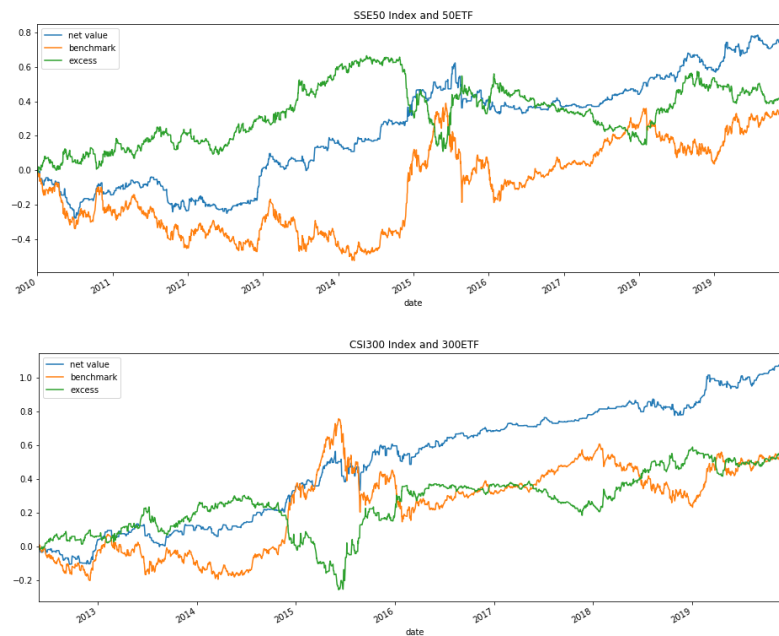


Figure4: Net values of strategies with day-close signal on ETFs and benchmarks.



Figure5: Drawdown of day-close signal on SSE50 and CSI300.

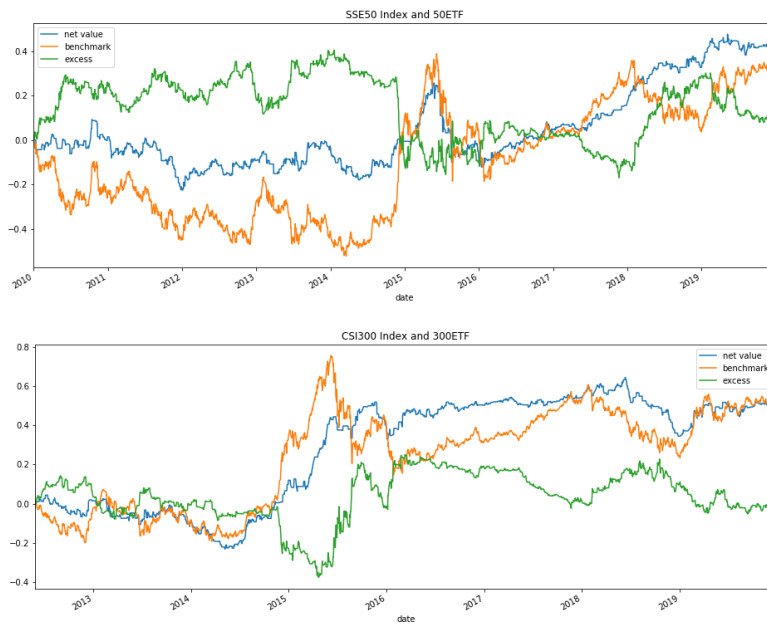


Figure6: Net values of strategies with volume-based signal on ETFs and benchmarks.



Figure7: Figure5: Drawdown of volume-based signal on SSE50 and CSI300.

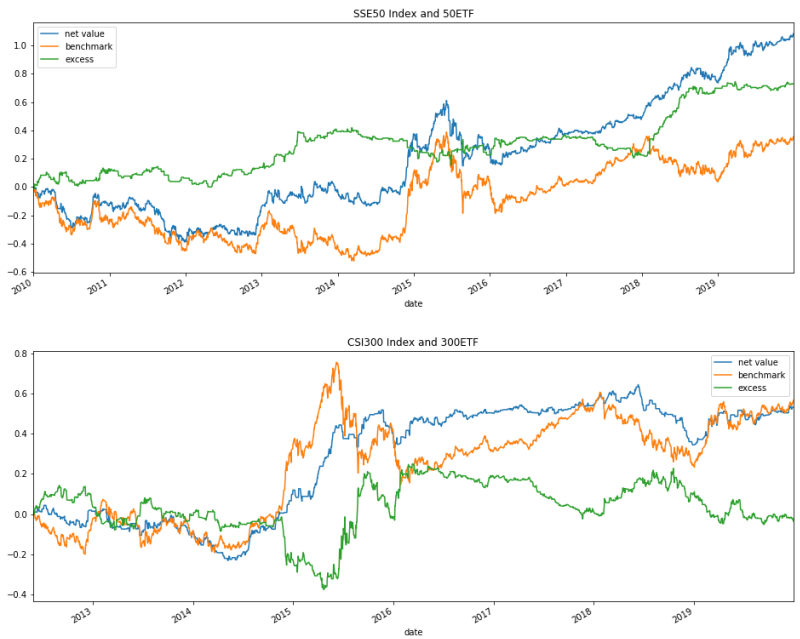


Figure8: Net values of strategies with combined signal on ETFs and benchmarks.

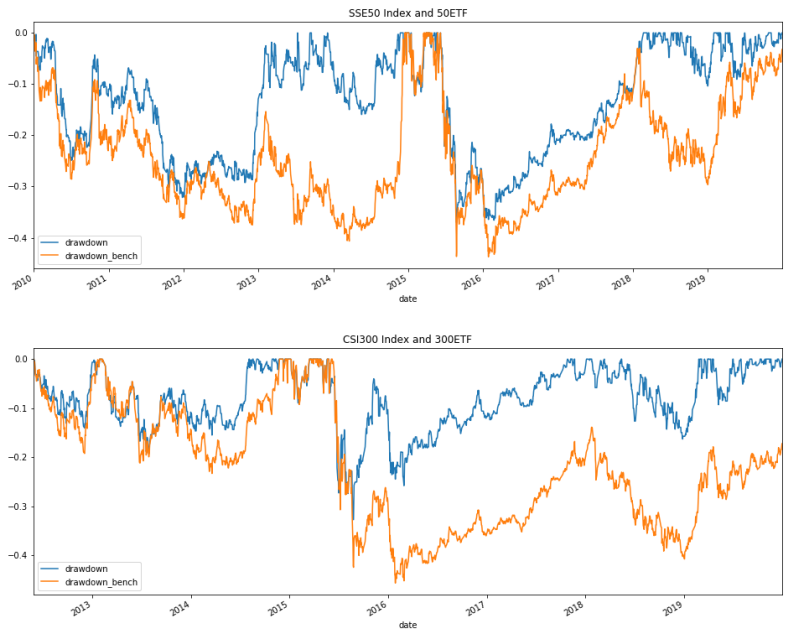


Figure9: Drawdown of combined signal on SSE50 and CSI300.