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Back-test on market Microstructure Order Book

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by

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Abstract

Traders nowadays are doing intraday trading by using parameterized trading strategies to provide the market with liquidity. Part of them use strategies associated with the market microstructure. This paper will mainly test empirically on Microstructure Order Book strategy to see if the Chinese A-share market is efficient or not. My empirical test mainly consists of two parts. First, I need to access industry-level data, which at least span half of the year. Then, using Python, a modern programming language, to clean the data. In the following, I need to write the code to do an analysis job to test a large wide of alternative parameters. Last, to calculate the Sharpe ratio and to select the combination of parameters to maximum the Sharpe ratio. As for the importance of this test, it would show whether an investor can get profits through algorithmic trading by picking up certain parameters.

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Introduction

The global financial market consists of investors who hold different investing philosophies. Some of them believe the "value investment", which means they will purchase assets at undervalued prices to realize their profits when the value of the assets is recognized by the whole market. According to Asness, Frazzini, Israel, and Moskowitz (2015), researchers have already studied this topic since the 1980s. However, with the development of high-performance computers, traders have more advanced means to take profits from extreme price movement within a short time.

This brand-new shift is brought by the high-frequency trading (also known as HFT). In the paper of Van Kervel and Menkveld (2019), it is argued that the participation of HFT is favorable for narrowing the bid-ask spread and improving the price efficiency. As Gomber and Haferkorn (2015) proposed, HFT should be regarded as a kind of evolution of the securities market in a natural way. In addition, the majority of trading strategies of HFT have a positive impact on market liquidity, i.e. market making strategy, and market efficiency, i.e. arbitrage strategies (Gomber&Haferkorn, 2015).

Plenty of strategies based on HFT have been devised for capturing profits in the financial market. High-frequency traders would employ different algorithms to calculate indicators that meet traders' interests. The complexity varies from different traders even though the core strategy behind these algorithms is similar. This paper would mainly focus on one specific strategy based on HFT, the Microstructure Order Book strategy. It's important to illustrate the concept of market microstructure. In short, the microstructure mainly studies three branches: price information and

discover, market structure and design, and information and disclosure (Marcus, 2018).

Tsantekidis et al. (2017) argued that one feasible way of taking profits is to detect the market price movement to maximize profit while minimizing the risk amount by observing data from the limit order book. Besides, it's also feasible to use data from the limit order book to predict the direction of following market order (Cartea, Donnelly & Jaimungal, 2018). More accurately, Cartea, Donnelly, and Jaimungal (2018) take advantage of information from the limit order book to conduct directional trades by using market orders.

There are researchers also interested in finding the optimal position for the limit order by using the signal from the limit order book. According to Guo, De Larrard and Ruan (2017), they studied the problem associated with optimal placement for limit orders.

In this paper, for Microstructure order book strategy, the test for parameters, which are crucial for devising the algorithm, is necessary. One important parameter, the Exponential Moving Average (EMA), is tested by Ju, Kim, and Lim (2019), whose result shows that there is discrepancy between short-term and long-term MA. Another important parameter is the standard deviation (STD), which is used to quantify the degree of deviation from the MA.

Furthermore, with the construction of MA and STD, it is easy to build the upper band, which is equal to MA plus several STDs, and lower band, which is derived by using MA minus several STDs. Intuitively, with the belief of mean reversion of price, a trader should open his position when the current price of an asset is out of the range

of upper band and lower band.

As for the connection between this thesis and the topic, if there are a pair of parameters that can make profits from the stock market, then the stock market is not efficient enough. In addition, the algorithm used in this paper is comparatively easy than those appearing in the literature review. Also, this paper mainly uses modern programming language to calculate big data from the order book to do back-test and find optimal pairs of parameters to make a profit. The result will be interpreted in a reader-friendly way to make it as comprehensible as possible.

Literature Review on Market Microstructure Order Book

It is necessary to show the how other papers can help me narrow down and build connections to my topic, Market Microstructure Order Book.

The concept of Market Microstructure has been explained by Marcus (2018). According to him, research on this field mainly focus on three branches: “price information and discover, market structure and design, and information and disclosure”. Price information and discover mainly concerns with how many information contained in the price of assets. Market structure and design mainly refer to trading rules and how these rules affect investors. In addition, information and disclosure refers to how market makers work in the market and how traders are affected by market makers.

Fohlin (2016) states that it is the market microstructure that causes the asymmetric information which cause traders try to maximize their own profits against other maker participants in the market. In addition, the market microstructure will make impact on the market especially when the market is experiencing unusual events (Fohlin, 2016).

Some researchers have tested the microstructure of U.S. Treasury Market, and they also estimate the price impact of trading in this market. The microstructure of U.S. Treasury has changed a lot because of the shift from voice-assisted brokers to electronic brokers (Fleming, Mizrach & Nguyen, 2018). In addition, according to Fleming, Mizrach and Nguyen (2018), price impact is very small, and it can be smaller if order book information is considered.

The application of Market Microstructure has to do with the high-frequency

trading (HFT). Due to computer control, narrow “time scale of microseconds”, investors have to recognize the importance of learning Market Microstructure which requires to design optimized trading strategies against other high-frequency traders (O’Hara, 2015). As O’Hara (2015) states, exchanges have to design its microstructure better so that it will attract more HFT traders because HFT has contributed more than half trading volume. Given that in a mature financial market institutional investors doing most of trading, so Van Kervel and Menkveld (2019) try to test if orders from large institutional investors are based on information by using microstructure technique.

Ryu (2017) in his paper recommends some variables to make the market microstructure model more comprehensive. Variables, including size of order, order duration, market liquidity and the cost of holding the inventory, are used for constructing a more comprehensive model. What’s more, according to Ryu (2017), the extension of these variables is useful because these variables can provide traders with economic meaning.

After introducing basic knowledge about Market Microstructure, it is necessary to illustrate how other papers to design their own indicators for improving profits. In *Enhancing Trading Strategies with Order Book Signals* (Cartea, Donnelly, & Jaimungal, 2018), a good measure is devised for predicting the sign of the market order (MO) for the following short time based on information from Limit Order Book (LOB). In detail, their measure can help investors predict the types of the next MO, such as buy and sell, and the price of the next MO. Such an improvement is quite

useful because it can direct investors to place their order well to increase the profits.

In addition, the advantage of use of the model in this paper can reduce adverse selection so that the profit will increase.

Considering that huge amount of data from LOB, so it is necessary to process data before analyzing it. The method used by Tsantekidis, Passalis, Tefas, Kannianen, Gabbouj and Iosifidis (2017) shows how these authors process huge LOB data to decrease the noise. The introduction of mid-price indicator and Exponential moving average indicator can be used for detecting if price movement occurs. Puljiz, Begušić and Kostanjčar (2018) show the result of empirical research about the prediction based on mid-price indicator by introducing limited order book model. Their predicted frequencies of upward price movement are similar to observed frequencies of upward price. However, when ask and bid orders are separated to calculate the estimating arrival and cancellation rate, their result is much worse than the situation where these orders are taken together (Puljiz, Begušić & Kostanjčar, 2018).

Ju, Kim and Lim (2019) use gradient analysis towards some important indicators in the microstructure of multiply markets. For LOB volumes, the result shows that when market goes down, the gradient of bid volume is negative and gradient of ask price is volume, which means more people want to sell their stocks. If the market goes up, then the sign of two gradients just reverse. They also test the change of Exponential moving average and show that when there is increase in long-term Exponential moving average, the best bid and ask price to have higher chance to go up.

Methodology

Generally, this paper will mimic the Microstructure Order Book strategy to back-test if there is a pair of parameters that can make profits in the Chinese A-share market.

In detail, the method used in this paper mainly consists of the generation of key indicators, selection model and the calculation of the Sharpe ratio. The generation of key indicators mainly refers to create indicators that can represent the trend of the market at the moment. The indicators measure how strong the buy side (sell side) now is, and they indicate which direction a trader should go. The selection model is used to pick up the data records which meet the requirement of the model maker, and the result from the model shows the moment when a trader should open his or her position. The last step is associated with calculating the Sharpe ratio, which quantifies how many returns can be earned by taking a unit risk.

Data would be collected from the database of Bloomberg, and they will be cleaned before putting it into the next step. In the analysis process, all data will serve for building the Bollinger Band, which consists of the upper band and the lower band. As introduced above, the upper band level would be equal to the sum of Exponential Moving Average (EMA) and the product of a constant and the rolling Standard Deviation (STD).

For EMA, the bigger the α is, the more sensitive the EMA to the recent price.

$$EMA_t = \alpha P_t + (1 - \alpha)EMA_{t-1}$$

$$EMA_t = \frac{\sum_{i=0}^n p_{t-i}(1-\alpha)^i}{\sum_{i=0}^n (1-\alpha)^i}$$

Suppose the window time is n, then,

$$Rolling\ Mean\ Value = \frac{\sum_{i=0}^n p_{t-i}}{n}$$

The rolling mean value would be used to replace the mean value in the calculation of STD. Suppose the current combination of parameters is window n, and the coefficient of STD is K, then the upper band level and the lower band level would be

$$Upperband\ Level = EMA_t + K * STD$$

$$Lowerband\ Level = EMA_t - K * STD$$

The materials involved in this paper are R and Python programming language, which would be used for processing the large volume of data.

As for limitation, the algorithm of EMA assigns little weights for the past price information. In a way, it reflects the current price information, but it also ignores the impacts of tailed-risk events because these events usually have long-term impacts. However, the weight of these events will quickly decrease due to the mechanism of the EMA.

In addition to the disadvantage of the mechanism of the EMA, the value of Lower band level is also quite low due to the special investment policy in the Chinese A-share market. It is difficult for investors to short selling in the Chinese A-share market, which means even though the traders are aware of the selling trend of the market, they have no immediate method to follow the selling trend to make a profit in the downside of the market.

The Sharpe ratio calculation is modified due to the complex process of modifying the risk-free interest rate. Traditionally, the Sharpe ratio's formula is:

$$Sharpe = \frac{R_p - R_f}{\sigma_p}$$

where R_p is the return of the portfolio, R_f is the risk-free interest return and σ_p is the standard deviation of the portfolio's excessive return. However, it is unnecessary to deduce the risk-free rate because the microstructure strategy is not used for cross-region markets. Thus, a modified Sharpe ratio is more useful, and the computer can process data faster without the more complex algorithm.

The modified Sharpe ratio is defined in this way:

$$Modified\ Sharpe = \frac{Ave_R_p}{\sigma_p}$$

Where the Ave_R_p means the average return rate per trading day, and the σ_p is the standard deviation of the portfolio's total return. In the following heatmap, all numerical values refer to the modified Sharpe ratio.

Data

● Row Data

All row data come from the Bloomberg Terminal, which provided historical limit book data. The dataset consists of sub-data from 30 stocks in the Chinese A-share market, which cover all information for half a year. Each dataset of one stock in the A-share market has 4 columns or 4 variables. It contains Time, Type, Price, and Size.

The following table shows an example of one record of the dataset.

No	Time	Type	Price	Size
1	2019/2/1 9:30:03	Bid	5.51	43,923
2	2019/2/1 9:30:03	Bid	5.51	23,453
3	2019/2/1 9:30:03	Bid	5.51	14,523
4	2019/2/1 9:30:04	Bid	5.52	12,652
5	2019/2/1 9:30:06	Bid	5.54	1,974

The row data has the following features which bring disadvantage for the back-test.

1. The time is not even. From the above table, it is known that we have 3 bid limit orders at the same time, 2019/2/1 9:30:03. When we generate the MA and STD, which require the time span parameter, for example, 500 seconds, as its argument, so the time must be distributed evenly. Thus, we have to condense all information from the limit order book at 2019/2/1 9:30:03 into one record.
2. The time recorded is not continuous. There is no bidder put their orders in 2019/2/1 9:30:05. So, we have to copy the information from last time to represent

the status of the moment that the dataset lacks.

- **Processing Row Data – Step: Generation of an indicator measuring the trend**

As mentioned above, this paper would adopt a simple algorithm to generate an indicator representing how strong the whole market is buying or selling. Therefore, an additional variable, Cumuindicator, is created to meet this need. Taking the Chinese A-share market's policy into consideration, this indicator has to return to 0 after the closing the market, and it will recalculate at the next trading day.

$$CumuIndicator = \sum_{Time(t)} Price_t \times Size_t \times Sign_t$$

Where t is in a certain trading day.

$$Sign_t = \begin{cases} 1, Type_t = Bid \\ -1, Type_t = Ask \end{cases}$$

By adopting the above algorithm, the row data would have an additional column:

No	Time	Type	Price	Size	CumuIndicator
1	2019/2/1 9:30:03	Bid	5.51	43,923	242015.73
2	2019/2/1 9:30:03	Bid	5.51	23,453	371241.76
3	2019/2/1 9:30:03	Bid	5.51	14,523	451263.49
4	2019/2/1 9:30:04	Bid	5.52	12,652	521102.53
5	2019/2/1 9:30:06	Bid	5.54	1,974	532038.49

Still, this table hasn't solved the problems mentioned above.

- **Processing Row Data – Step 2: Adjustment**

The ideal dataset after cleaning should be like this one:

No	Time	Type	Price	Size	CumuIndicator
1	2019/2/1 9:30:03	Bid	5.51	81,899	451263.49
2	2019/2/1 9:30:04	Bid	5.52	12,652	521102.53
3	2019/2/1 9:30:05	Bid	5.52	12,652	521102.53
4	2019/2/1 9:30:06	Bid	5.54	1,974	532038.49

The new No.1 record is generated by sum all size of 2019/2/1 9:30:03 when the prices are the same. If the prices are not the same for all bid orders in the same time period, then the last price information will be used for the purpose of approximation.

The new No.2 record is the same as the original No.4 record. Also, the new No.4 record is the same as the original No.5 record in the dataset. The generated No.3 record in the new table is created by copying all information except the time from the new No.2 record in the second table.

Analysis and Findings

After running the code through Python and generating the heatmap for the historical performance of 30 stocks by Excel, there are 5 out of 30 stocks are qualified for the microstructure strategy. There are also 8 stocks proved to have significant positive return.

The criteria for the microstructure strategy are to have more than 30 trading volume and the Sharpe ratio which is larger than 2. Here is the overall table to summarize all result information from the empirical test.

Code	Optimal Parameters		
	EMA	STD	Sharpe
600150	2400	5.0	1.85426
600410	2700	2.5	1.8620
600703	3700	3.5	2.15135
600536	4900	4.0	2.27605
601318	2000	4.5	1.19426
601155	2400	3.0	3.04656
601066	1700	5.0	4.12903
600585	4700	3.0	2.29217

Table 1 Overview Testing Result

The table 1 only contains the stocks which have positive Sharpe ratios. Due to the theme of this paper is about microstructure strategy, stocks which meet the criteria of this trading strategy will be discussed in detail.

For stock code 600503, the heatmap, which is the figure 1(a), shows us that the best Sharpe ratio occurs when EMA's parameter is 4900 and STD's parameter is 4. The reason to pick up (4900, 4) has to do with the stability. From the figure 1(a), it is known to us that other Sharpe ratios which are around the best one selected are also

high and positive. Thus, even though the market changes, the return would also be relative stable.

For stock code 600585, the heatmap, which is the figure 2(a), shows us that the best Sharpe ratio occurs when EMA's parameter is 4700 and STD's parameter is 3. The mechanism behind this selection is the same as the code 600503.

For stock code 600703, the heatmap, which is the figure 3(a), shows us that the best Sharpe ratio occurs when EMA's parameter is 3700 and STD's parameter is 3.5. Reader may feel confused about this value because the Sharpe ratios from other combinations are even larger. An important concept, the significant statistical meaning, is worth of emphasizing. In this case, a high Sharpe ratio is preferred but its number of trading has to be larger than 30, which indicates the sample size has to be larger otherwise this Sharpe ratio is not meaningful.

For stock code 601066, the heatmap, which is the figure 4(a), shows us that the best Sharpe ratio occurs when EMA's parameter is 1700 and STD's parameter is 5. The selected Sharpe ratio, 4.129, is the largest value among all calculated Sharpe ratios in this table and its trading volume is larger than 30, which leads to the combination (1700,5) the best choice.

For stock code 601155, the heatmap, which is the figure 5(a), shows us that the best Sharpe ratio occurs when EMA's parameter is 2400 and STD's parameter is 3. The mechanism of this selection is similar to the one of the stock with code 600703.

After showing the result for these selected stocks, it is necessary to show more in detail to illustrate why the market is not efficient enough.

For all table plot, for example, the figure 1(b), all CumuIndicator numbers have been converted into the log value with 10 as the base. In addition, the y-axis is the rank of the observations with processed CumuIndicator values. For instance, 10% means records with all top 10% processed Cumuindicator values. This mechanism applies to all rest table plots, such as the figure 2(b), 3(b), 4(b) and 5(b).

For figure 1(b), it is known to us that the top processed CumuIndicators will occur between April and May, which means that investors in the market trend to buy the stock 600536 between April and May. In addition, the negative processed CumuIndicator value occurs in March and May, which means that investors want to sell their stock in March and May. This result can also be confirmed by the figure 1(c). Furthermore, if the Time variable is taken into consideration, it is seen that the higher log CumuIndicator will occur after 13:30, which shows the investors are likely to purchase this stock in the afternoon session. Another phenomenon is noticeable, it is during the afternoon session when investors want to sell the stock 600536 because the lowest log CumuIndicator values occurs in this period.

For figure 2(b), the highest values occur in April to June, and the lowest values occur in March to April, which shows that the investors want to sell the stock and then they want to buy the stock again. This result can also be reflected in the figure 2(c). In term of the Time variable, a phenomenon is noticeable. The highest and the lowest values occur in the afternoon session. Or more detailed, they all occur in the moment when the market is close to the close time.

For figure 3(b), the top 2% highest values occur in March and July, and lowest values occur in March and April. This result can also be reflected in the figure 3(c). In term of the Time variable, the highest and the lowest values are more likely to occur in the afternoon session. Or more specifically, they are likely to happen in the moment when it's close to the end of the trading day.

For figure 4(b), the top 1% highest values occur in March and April and the lowest values occur in March and June. This result can also be confirmed by the figure 4(c). What makes the stock 601066 different from other stocks mentioned above has to do with the Time variable. The highest log Cumuindicator occurs in the beginning of the afternoon session, but the lowest one is likely to happen in the end of the trading day.

For figure 5(b), the top 1% highest value occurs in July and the lowest values are likely to happen in April and July. This result can be confirmed by the figure 5(c). In term of the Time variable, all lowest values are likely to happen in the end of the market, but the highest values are distributed relatively evenly from the beginning of the morning session to the end of the afternoon session.

All analysis focusing on the likelihood of the processed CumuIndicator in terms of specific date and specific time period shows that the market mood towards buying and selling are biased.

Conclusion

From the above analysis and findings, further detailed conclusions about the microstructure strategy is needed to illustrate the feasibility of this strategies.

Combined with the result from the last section, an investor who conducts the microstructure strategy is able to design the algorithm which detects the mood the market to get the profits. The core of this strategy is to know the mood the market within a short time in advance so that the investor can buy stocks at a lower price earlier and then sell the stocks later at a higher price which is driven by the mood of the market.

The feasibility of this strategy relies on the inefficient market, which is caused by many factors such as the intervention from regulatory institutions and large number of irrational individual investors in the market. In addition to these factors mentioned above, an algorithm that is quick enough to calculate the market mood is also important. What's more, for the stocks which have been proved to have the optimal combination of parameters, it's not sufficient to say that the trader using the microstructure can get profit from it. The competition among all traders is severe and it may cause some of traders to suffer losses because of commission fees and unideal position they enter. For example, the optimal combination for stock 601066 is (1700, 5.0). In reality, if a stock's current price leaves the rolling average price about 5 standard deviation, every investor who believe the feasibility of the microstructure strategy will compete to buy the stocks, which leads to the situation where some other traders may buy the stock at a much higher level than they thought. This is another core of the microstructure strategy – the speed. Since the microstructure strategy plays

an important part in the high-frequency trading, in fact this trading strategy is common for most of the practitioners in this industry, which means the profit space left will be smaller and smaller.

Limitations and Contributions

● Limitations

This back-test does have several limitations, some of which come from the inherent institute of A-share market, some of which belong to the method I used for cleaning data and calculating the indicators

Inherent limitations mainly lay down the inflexibility of short selling in the A-share market, which leads to a situation where the trader can only wait when the whole market is selling. In A-share market, investors have limited access to short selling stocks because the minimum level is 20 million CNY and investors are limited to short selling when the market is in the serious crisis.

Other limitations are associated with the processing method of row data. As mentioned above, for those records whose time is the same, the "condensing" way is to take the information from the last record, which would cause the lack of records with extreme price and size information. This approximation method will cause the accuracy of the back-test.

The size of the dataset is not large enough. As mentioned above, the dataset only covers half-a-year span, which is less than the time for a complete business cycle. Therefore, the result generated by using this relatively small dataset may not suit for the whole business cycle.

This paper only provides the readers with the result of back-testing. Thus, the Sharpe ratio calculated by this paper is only an ideal value, which means in reality, the true performance will be affected by other factors, such as the competition from other traders who adopt a similar trading strategy. In this paper, it is assumed that the

investor who conducts the microstructure strategy is able to buy the stock immediately after the price is deviated to the significant statistical level. However, in reality, lots of other investors in the high-frequency fund would also compete to open their long position if the price deviates to the abnormal level, which would lead to lower profits for each participant using the microstructure strategy.

- **Contributions**

Compared with papers which adopt advanced and complicated algorithm to predict the tendency of the trades, this paper adopts a much simpler algorithm to calculate the indicator, which would be friendly for readers with basic quantitative knowledge and financial knowledge. At least, this paper would give readers the sense of trading by taking strategies based on High-Frequency Trading, which may pave the way for further study.

In addition, this paper would also test if the Chinese A-share market is efficiency enough. If it's quiet efficiency, then the expected result should be negative because of the existence of fees for trading. If it is not efficient enough, the result should show lots of feasible combinations of parameters that lead to a positive Sharpe ratio.

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Appendix

Sharpe EMA	STD								
	1.5	2	2.5	3	3.5	4	4.5	5	5.5
500	-6.0612	-5.3371	-4.9528	-3.2272	-2.3398	-0.9792	-1.7114	-2.1543	-2.9786
600	-5.3783	-3.9455	-3.59	-3.6094	-2.2042	-1.787	-1.7867	-2.9444	-2.2903
700	-4.5175	-2.9036	-3.1191	-3.0297	-1.585	-1.7328	-0.1821	-1.1347	-0.9174
800	-3.8945	-2.8466	-2.8602	-3.2736	-1.6057	-1.4352	-0.9628	-0.5842	-0.2034
900	-3.2911	-2.3712	-2.3413	-1.9276	-2.2992	-0.7977	-0.5693	-0.2495	0.17806
1000	-3.2244	-3.0979	-2.7344	-2.7471	-2.58	-2.0807	-0.6696	-0.4801	-0.7206
1100	-3.5546	-2.8689	-2.4368	-2.3401	-2.1253	-0.9875	-0.1697	0.60331	0.04641
1200	-3.7904	-2.9062	-2.278	-2.0863	-2.0406	-1.1119	1.54869	1.35384	1.09097
1300	-3.0264	-2.2556	-2.4725	-1.915	-2.1441	-0.9566	1.69755	1.67903	0.57477
1400	-2.9095	-2.1718	-1.9848	-2.1249	-1.749	-1.3473	0.37948	0.8161	0.73881
1500	-2.5081	-2.0779	-1.8879	-1.453	-1.1191	-1.211	0.33704	0.74863	1.74918
1600	-2.1463	-1.6566	-1.4691	-1.2343	-0.2707	0.05328	0.84302	0.68776	0.91556
1700	-1.7251	-1.3988	-1.4676	-1.2047	-0.2049	0.56736	0.78657	0.39831	1.14804
1800	-2.0946	-1.5559	-1.8561	-1.3566	0.25929	0.15909	0.26434	0.5863	1.00135
1900	-1.5812	-1.2601	-1.6987	-1.0302	-0.4537	0.05957	0.25824	0.0205	0.64849
2000	-1.7773	-0.9794	-1.6237	-0.9365	-0.099	0.24002	0.05337	0.16768	0.75035
2100	-1.6078	-0.735	-1.3828	-0.8509	-0.1873	0.22654	0.15094	0.41731	1.16777
2200	-1.3218	-0.5031	-1.3692	-0.7484	-0.4679	0.40171	0.41176	1.09465	1.47095
2300	-1.398	-0.7489	-1.4043	-0.9376	-0.1817	0.50352	0.77904	1.52789	0.80145
2400	-1.3249	-1.144	-1.5102	-0.8697	0.04603	0.93568	1.15212	0.46758	0.04633
2500	-1.4264	-1.366	-1.6479	-1.0958	-0.7777	0.92132	1.06313	0.64535	-0.0175
2600	-1.7228	-1.6596	-1.614	-1.413	-0.7503	0.92698	1.69826	1.00709	-0.0659
2700	-1.7163	-1.2665	-1.356	-1.1584	-0.5321	1.18008	1.77074	1.33484	0.23348
2800	-1.9578	-1.0682	-0.9917	-1.1127	-0.809	1.19668	1.26606	1.09086	-0.1577
2900	-1.6867	-1.1888	-0.699	-1.3911	-0.9265	0.9642	1.94498	0.64898	0.56271
3000	-1.7537	-1.3786	-0.8095	-1.533	-1.3587	0.35046	1.69401	0.83906	0.45183
3100	-1.8955	-1.4348	-0.9443	-1.5153	-0.9283	0.52581	1.82996	0.80018	0.44447
3200	-1.7979	-1.448	-0.8449	-1.2488	-0.7315	0.74725	1.87378	0.88785	0.53187
3300	-1.4578	-1.1716	-1.0126	-1.3497	-0.3383	0.44489	1.76095	0.87545	0.43801
3400	-1.6355	-1.0049	-1.0064	-1.3109	-0.0815	0.50321	1.26593	0.86972	0.404
3500	-2.021	-1.4604	-1.055	-1.5317	-0.6834	0.34333	1.29926	0.91925	0.09576
3600	-1.9482	-1.7585	-1.2245	-0.8829	-0.2527	-0.5635	2.03138	0.51403	0.33983
3700	-1.8562	-1.5855	-0.9083	-0.8077	-0.1938	-0.3019	1.10337	0.03995	0.3084
3800	-1.4865	-1.5216	-1.2207	-0.9424	-0.1461	-0.4467	0.6446	0.26619	0.25766
3900	-1.4328	-1.5563	-1.5075	-1.0195	0.025	-0.4907	0.98617	-0.1668	0.26442
4000	-1.343	-1.6615	-1.086	-0.929	-0.6269	-0.6128	0.9071	0.31257	-0.0168
4100	-1.019	-1.2295	-0.6545	-0.3943	-0.2239	-0.1136	0.73071	0.28988	0.28803
4200	-1.0589	-1.3282	-0.7223	-0.6069	0.3071	-0.2783	0.67292	1.38127	-0.2106
4300	-0.9	-1.3432	-0.9736	-0.6706	0.5634	-0.2434	1.31802	1.25023	-0.2106
4400	-0.6938	-1.317	-1.0593	-0.5135	0.48894	-0.225	1.22726	1.32677	0.4231
4500	-0.9728	-1.4326	-1.2985	-0.8553	0.23522	0.93214	1.13706	1.43115	0.40024
4600	-0.9241	-1.4719	-1.3932	-0.8969	0.06124	1.82392	0.91917	1.54771	0.41718
4700	-1.5816	-1.7353	-1.1042	-0.8985	0.97922	1.78549	0.87628	1.52428	0.41718
4800	-1.2606	-1.4268	-0.783	-0.9064	1.47194	1.99629	1.2812	1.47745	0.27031
4900	-0.8899	-1.2763	-0.9339	-0.4438	1.37551	2.27605	1.29056	1.58271	0.27031
5000	-1.1631	-1.3371	-0.9337	0.30952	1.43885	1.99366	2.0238	1.50201	0.27031

Figure 1(a): 600536 Heatmap

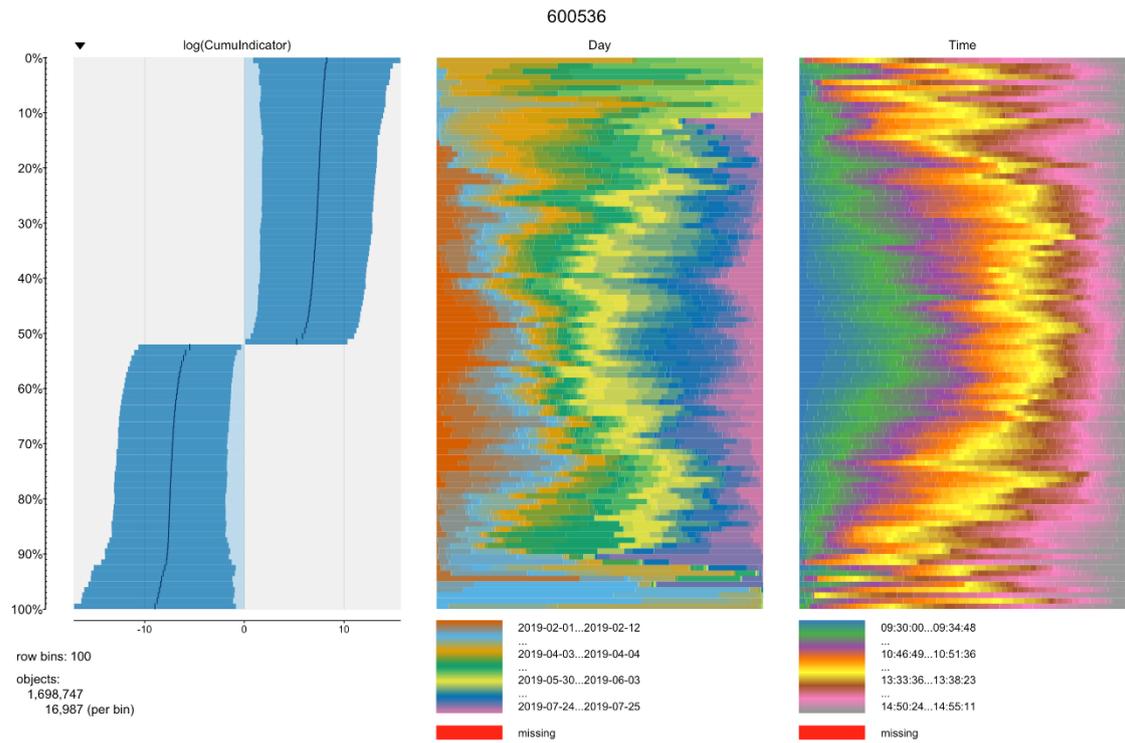


Figure 1(b): 600536 Table Plot

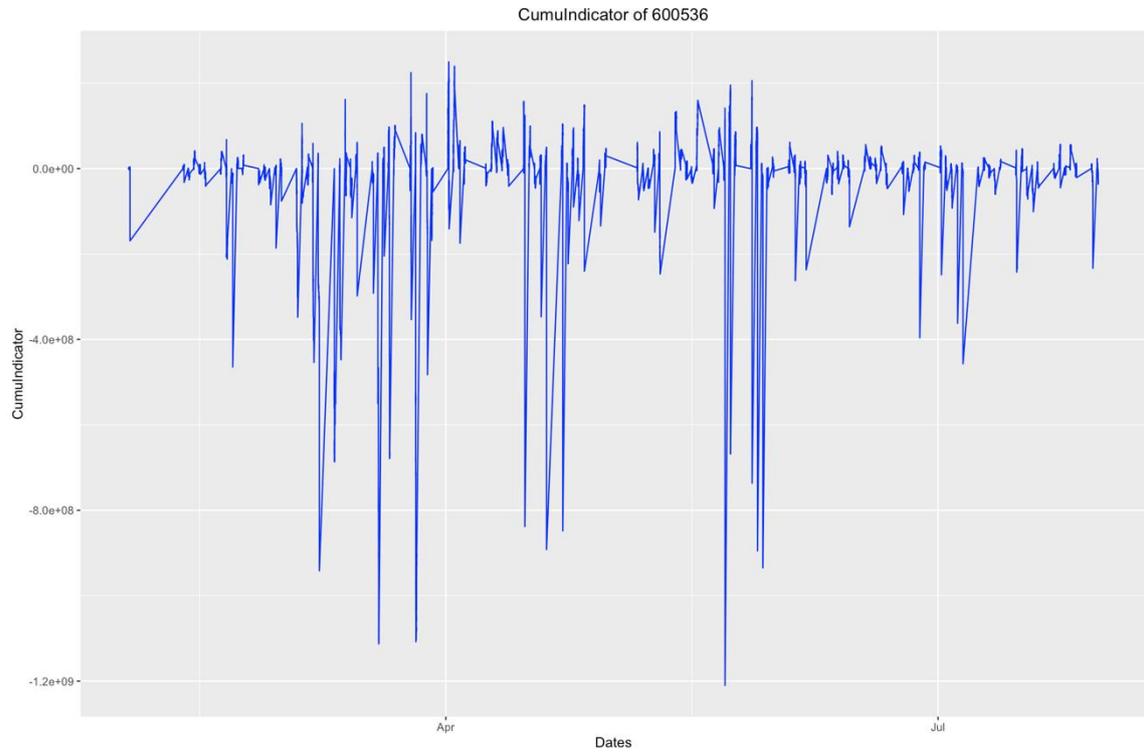


Figure 1(c): 600536 Cumuindocator

Sharpe EMA	STD								
	1.5	2	2.5	3	3.5	4	4.5	5	5.5
500	-19.947	-17.069	-13.636	-9.1083	-6.8814	-4.5684	-2.9577	-2.6049	-1.5964
600	-16.15	-13.755	-11.581	-8.4266	-6.9997	-5.346	-2.8636	-1.4591	-0.679
700	-14.333	-12.985	-10.289	-7.9049	-6.2436	-5.2424	-2.9159	-1.3867	-1.9111
800	-12.763	-10.638	-8.1108	-6.7797	-4.7065	-3.9725	-2.152	-1.565	-1.6538
900	-11.12	-8.5481	-6.65	-5.8739	-4.6887	-4.7553	-4.2272	-1.8639	-1.9936
1000	-10.153	-7.8759	-6.592	-5.4989	-4.358	-4.3112	-4.4658	-3.0842	-1.0437
1100	-8.1072	-6.4913	-5.2026	-4.3956	-4.0304	-4.0694	-4.4465	-2.1443	-1.1738
1200	-7.6935	-5.6245	-5.077	-4.5218	-5.5655	-4.2704	-4.2336	-2.0335	-1.5633
1300	-7.9025	-5.724	-5.768	-4.9217	-4.2651	-4.7376	-3.2774	-2.5755	-2.6438
1400	-7.356	-5.3183	-4.9936	-3.9996	-3.9631	-3.0592	-2.7957	-3.5061	-2.2576
1500	-6.9612	-4.2475	-4.4555	-3.1169	-3.2835	-3.8917	-4.4003	-2.623	-2.5825
1600	-6.3909	-4.4273	-3.2824	-3.3912	-4.09	-4.3658	-3.7357	-2.4277	-2.422
1700	-5.4924	-4.0414	-2.9027	-3.2223	-2.8672	-3.7866	-3.8938	-2.6764	-2.0851
1800	-5.4963	-3.9135	-3.4264	-3.1648	-3.6621	-3.9955	-3.6617	-3.3197	-1.7586
1900	-5.4373	-3.2645	-3.3288	-3.2547	-4.0394	-4.2467	-2.2063	-3.192	-2.1006
2000	-4.9162	-3.1933	-3.7119	-3.4655	-4.4117	-4.1567	-2.9331	-3.4799	-1.3751
2100	-4.4195	-3.3862	-3.9538	-3.4036	-4.4539	-3.9107	-3.2908	-2.8527	-0.8583
2200	-4.7555	-3.7588	-3.2558	-2.5275	-4.3328	-2.9158	-3.1507	-2.1647	-0.8735
2300	-5.204	-3.9155	-3.1366	-2.4094	-3.3935	-2.4453	-2.4562	-1.3859	-1.0095
2400	-5.3618	-4.4327	-3.2809	-3.5707	-2.6782	-2.4622	-1.8652	-1.989	-1.7667
2500	-4.9012	-4.3715	-3.4104	-2.5914	-2.0744	-2.4208	-2.1911	-2.0044	-1.7838
2600	-4.995	-4.1145	-2.8425	-2.0851	-2.0642	-2.1371	-2.5867	-1.9203	-1.6017
2700	-5.1369	-4.1282	-2.2619	-1.9139	-1.3603	-2.1778	-2.3166	-1.5618	-1.5973
2800	-5.2607	-3.9117	-2.5022	-1.9241	-2.1471	-2.5651	-2.7273	-2.3456	-2.3202
2900	-4.879	-3.9331	-2.3491	-2.2163	-2.7301	-2.5475	-2.5416	-3.1373	-2.2957
3000	-4.8276	-4.0413	-2.3368	-2.6797	-2.1975	-3.0604	-2.8319	-2.6566	-2.1886
3100	-4.7902	-3.8981	-2.4359	-1.4943	-1.9088	-2.2585	-2.6555	-2.3321	-1.651
3200	-5.1021	-3.6005	-2.9636	-1.4093	-1.9826	-2.0099	-2.4837	-2.6972	-2.084
3300	-4.0441	-3.0097	-1.8511	-0.6367	-1.696	-2.0997	-2.716	-2.2281	-1.9637
3400	-3.8225	-2.9402	-1.5337	-0.1516	-1.3149	-1.8331	-2.2914	-2.205	-1.9796
3500	-3.4107	-3.0429	-1.2094	0.05031	-1.2714	-1.9027	-1.6981	-1.0763	-1.9473
3600	-3.8756	-2.9415	-0.362	0.32627	-0.3894	-1.6227	-1.7804	-1.1171	-1.9711
3700	-3.2476	-1.2504	-0.2623	0.48818	-0.3271	-1.0997	-1.1294	-1.1452	-1.9021
3800	-3.1373	-1.3351	-0.2454	0.33455	-0.4996	-1.3598	-0.9675	-1.0218	-1.9124
3900	-2.3243	-1.0724	-0.2261	0.18628	-0.2978	-1.6692	-0.9332	-1.0815	-1.9086
4000	-1.8864	-0.8577	-0.3209	0.81169	0.94772	-1.5914	-0.8547	-1.1949	-1.8963
4100	-1.3618	-0.6352	-0.0799	1.03332	1.29906	-1.6001	-0.7409	-1.1517	-1.9412
4200	-1.4331	-0.4203	0.18074	1.03872	2.00162	-1.6488	-0.7353	-2.0841	-1.4305
4300	-1.4099	-0.7483	0.44774	1.27865	2.03547	-1.3049	-0.866	-1.5905	-1.4305
4400	-0.5544	-0.4418	0.99728	1.64683	1.92038	-1.4832	-1.6952	-1.5905	-1.4305
4500	-0.9757	-0.0441	0.60147	1.75408	1.91432	-0.813	-1.9387	-1.6142	-1.4305
4600	-1.3498	-0.4174	0.54926	1.68422	1.56379	-0.0631	-1.3593	-1.4538	-1.4299
4700	-1.5251	-0.2059	0.27836	2.29217	1.56415	-0.0622	-1.3825	-1.7873	0.12634
4800	-1.1378	-0.0859	0.50887	2.28476	1.99399	-0.0909	-1.5148	-0.0337	0.12634
4900	-1.0096	0.02355	0.55973	2.2558	2.0854	-0.3465	1.06996	-0.0337	0.12634
5000	-0.7547	-0.1938	0.46168	1.45951	2.01046	-0.459	0.15681	-0.0337	0.12634

Figure 2(a): 600585 Heatmap

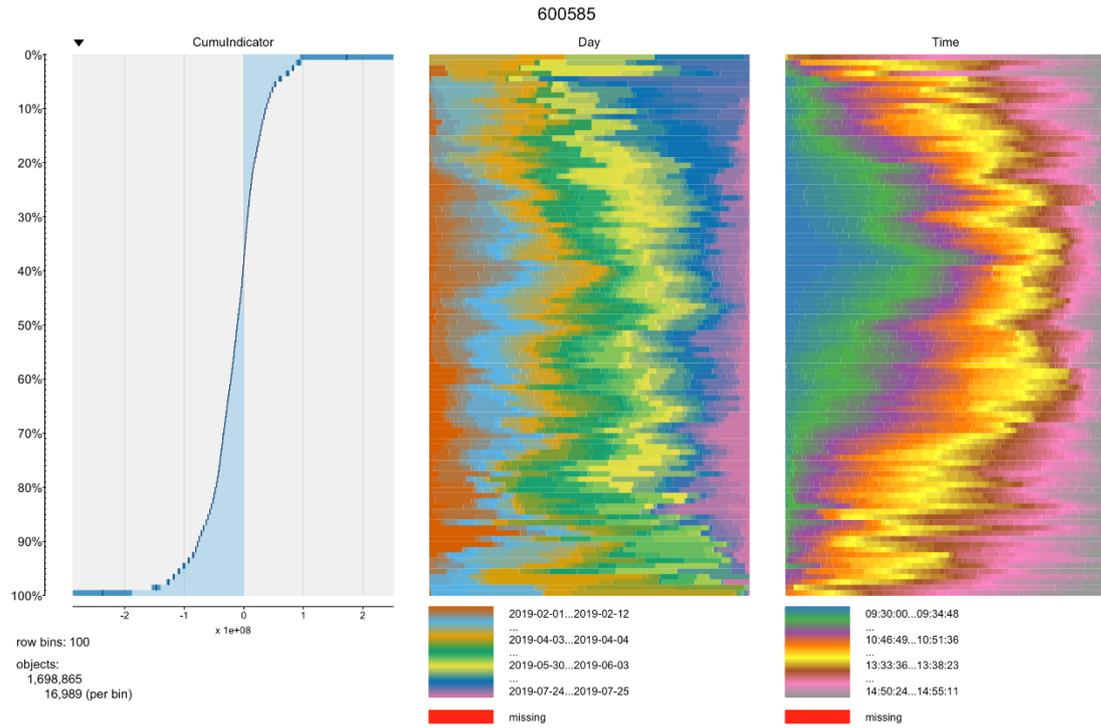


Figure 2(b): 600585 Table Plot

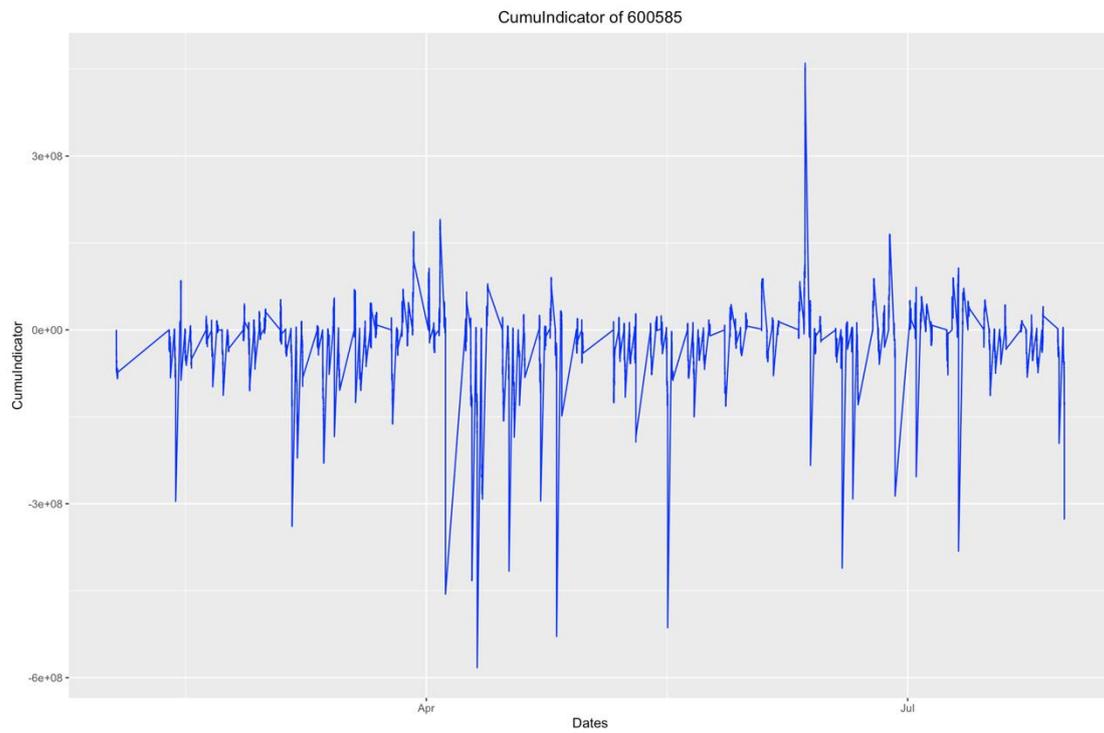


Figure 2(c): 600585 Cumuindicator

Sharpe EMA	STD								
	1.5	2	2.5	3	3.5	4	4.5	5	5.5
500	-15.7990	-14.2743	-11.0188	-7.8766	-5.3295	-2.7777	-1.8338	-1.4548	-0.8976
600	-13.1154	-11.1286	-9.3171	-5.8643	-4.3571	-2.7104	-2.0296	-1.2257	-1.5811
700	-10.2039	-8.6095	-6.8301	-4.0791	-2.9035	-2.0109	-1.8515	-0.7382	-1.4657
800	-9.1060	-7.1242	-6.1243	-4.1210	-2.7707	-2.3640	-2.4768	-1.7774	-1.6354
900	-7.3528	-5.8589	-5.1025	-3.7723	-1.0299	-2.0533	-1.0766	-0.4154	-0.1512
1000	-6.9612	-5.6440	-5.3091	-3.3571	-0.9984	-1.3833	-1.8483	-1.5074	-0.9269
1100	-7.3490	-5.6107	-4.6583	-2.9131	-1.4364	-1.3549	-0.7368	-1.2186	-0.0062
1200	-6.4034	-5.5211	-4.2444	-3.4730	-1.5216	-0.7042	0.0114	0.1013	0.6745
1300	-5.5307	-4.0511	-3.2440	-2.1323	-0.9450	0.0961	1.2614	1.1890	1.0792
1400	-4.8246	-4.1696	-3.0148	-1.8588	-1.7696	-0.1462	0.5754	-0.1295	0.1688
1500	-4.3023	-3.6155	-2.2780	-1.3796	-1.1275	-0.1560	0.4392	1.3228	0.1610
1600	-3.3198	-2.4191	-1.6564	-0.8558	-0.4556	0.3075	0.6454	1.3360	1.0682
1700	-3.6502	-2.7480	-2.1301	-0.4889	-1.1191	1.2037	1.8668	1.1979	1.0442
1800	-3.9140	-2.9215	-1.9713	-1.0030	-0.9005	1.3883	1.9948	1.4229	0.8245
1900	-3.8656	-2.8456	-2.4205	-1.2744	-0.2826	1.1648	1.6416	1.1123	0.6273
2000	-3.2767	-3.5082	-2.6877	-0.8282	0.0380	1.1836	1.9931	1.5662	0.6541
2100	-3.5574	-3.4735	-2.8792	-0.8616	0.6406	1.9138	1.9677	1.6663	0.5613
2200	-2.9954	-2.9713	-2.7911	-0.7593	0.7167	1.8412	0.7820	0.3986	-0.0599
2300	-3.3526	-2.6508	-2.5971	-0.1300	0.4677	0.9243	1.1089	0.6890	1.6728
2400	-3.1682	-2.5327	-2.2340	-0.6104	-0.7714	0.5970	0.6827	1.0423	0.8847
2500	-2.5406	-2.3487	-1.4883	-0.3647	-0.9519	0.7442	1.0673	0.9364	0.6816
2600	-2.8124	-2.0030	-0.9876	0.0103	-0.3501	0.3026	1.1845	0.9340	0.7411
2700	-1.9500	-1.1034	-0.5996	-0.1270	-0.9401	1.1847	1.2563	1.7622	0.6581
2800	-2.4213	-1.8294	-0.6059	-0.4592	-0.7336	1.1648	0.7881	1.1351	0.5007
2900	-2.3713	-1.5228	-0.5866	-0.4485	-0.4358	0.7069	1.0897	1.0129	0.7933
3000	-2.1785	-0.9034	-0.3010	-0.2534	-0.8591	1.5966	1.0200	0.8563	0.9760
3100	-2.1556	-0.9424	-0.2622	-0.7695	-0.7526	0.9812	0.7345	0.8843	1.3998
3200	-1.5270	-0.5795	-0.0636	0.0218	-0.3991	1.3037	1.8880	1.8928	1.2769
3300	-1.7526	-0.6816	-0.0647	-0.2014	0.0482	1.9633	2.3511	1.9850	1.4260
3400	-1.0309	-0.4481	0.5199	0.3528	1.3186	1.9889	2.5681	2.2646	1.9107
3500	-1.4309	-0.8273	0.0826	0.7852	1.8510	1.8597	2.2435	2.2897	1.9107
3600	-1.3390	-0.7347	0.2791	0.6164	1.9808	1.9101	2.3241	2.0741	1.7201
3700	-1.1695	-0.3532	0.4018	0.9076	2.1513	2.2875	2.3257	2.2081	1.7823
3800	-1.2473	-0.3761	0.4443	0.9819	2.1065	2.0280	2.2533	1.9012	0.9789
3900	-1.0368	-0.4480	0.5149	1.0869	1.5195	1.7905	2.2587	1.8933	0.4336
4000	-0.9996	0.1165	0.6523	0.8930	1.3146	1.7284	2.0616	1.4498	0.0242
4100	-1.1998	-0.3547	0.5503	0.7145	1.4556	1.5805	1.8164	1.5655	0.0602
4200	-1.6854	-0.7920	0.4714	0.8072	1.1265	2.0361	2.3067	1.9161	0.0602
4300	-1.3039	-0.4149	0.6944	0.9287	1.0694	1.5755	2.3105	1.8994	0.6569
4400	-1.4968	-0.6205	0.5578	0.5807	1.3223	1.2610	2.2501	1.8265	0.6126
4500	-1.2780	-1.0869	0.4561	0.6849	1.5231	1.4950	2.2850	1.7558	0.7404
4600	-1.2905	-0.4828	0.6962	0.4950	1.3728	1.6023	2.0541	2.1082	0.7404
4700	-1.0552	-0.2750	0.9815	0.8366	0.9244	1.6450	2.4630	2.1082	0.8505
4800	-0.9940	-0.4134	1.2118	1.0926	0.7810	1.4678	2.3128	2.0795	0.8714
4900	-0.6637	0.1186	1.2073	0.8629	0.7838	1.3939	2.3448	2.0791	0.9520
5000	-0.6765	0.2434	1.3551	0.7932	0.6777	1.4088	2.3383	2.0791	0.5784

Figure 3(a): 600703 Heatmap

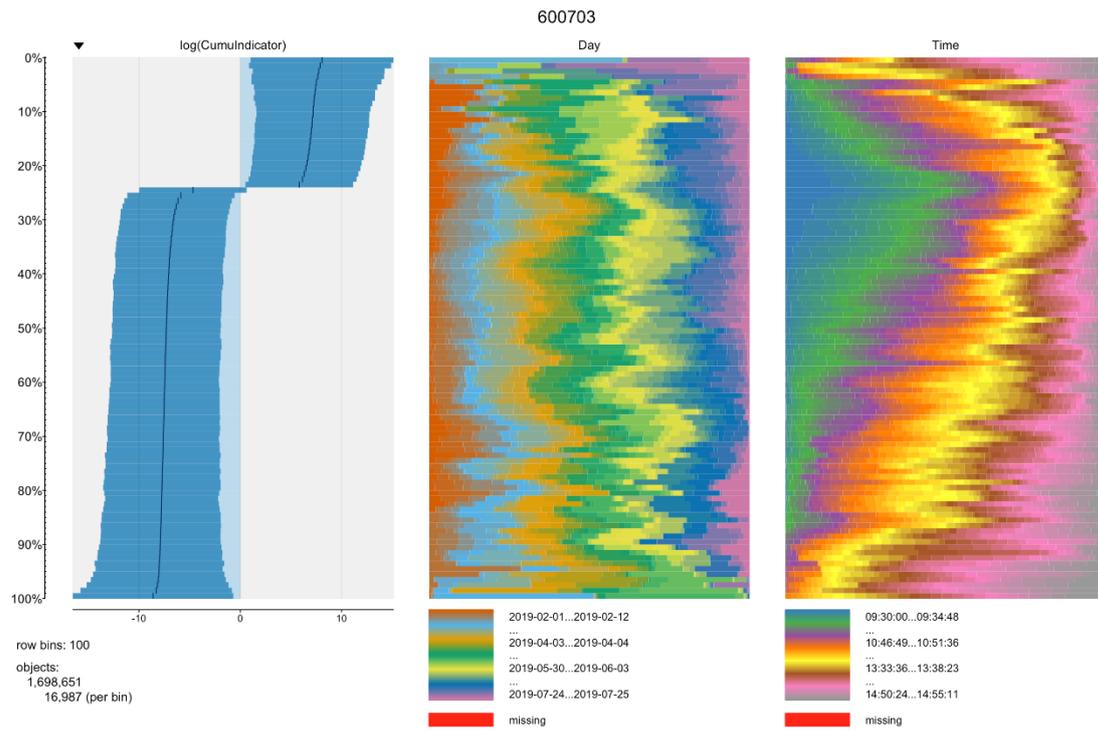


Figure 3(b): 600703 Table Plot

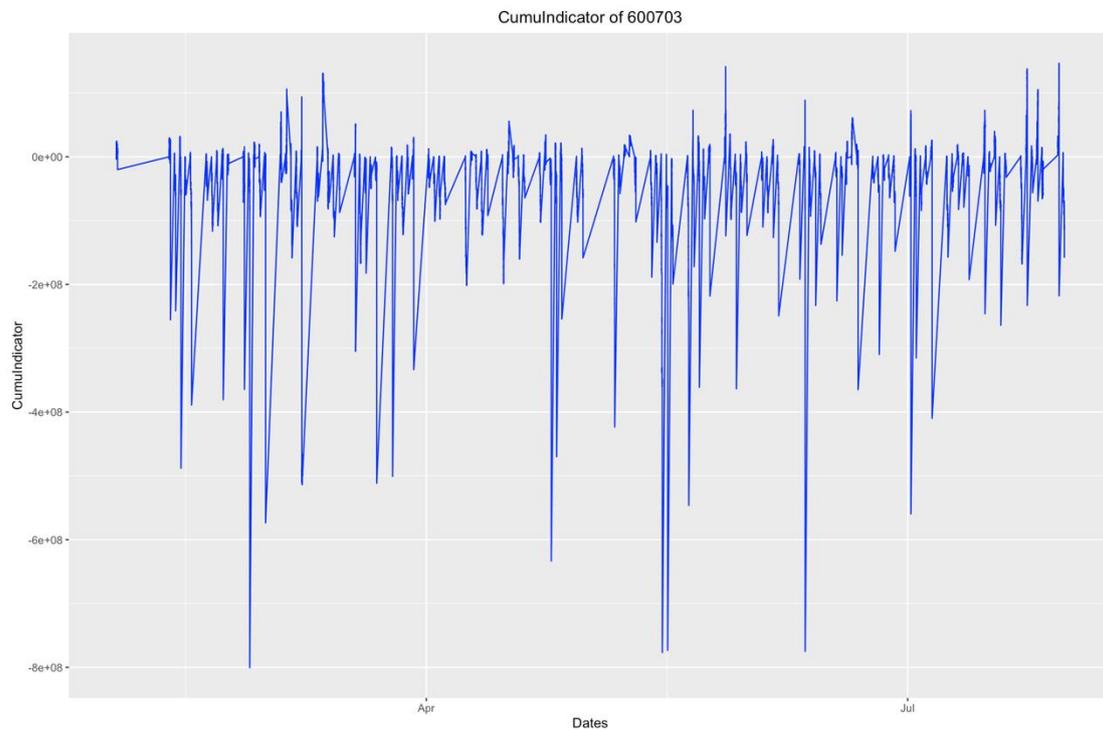


Figure 3(c): 600703 Cumuindicator

Sharpe EMA	STD								
	1.5	2	2.5	3	3.5	4	4.5	5	5.5
500	-6.151	-4.6869	-2.9765	-0.837	0.25599	1.83684	2.08462	1.49576	-0.0658
600	-4.0255	-3.157	-1.0791	0.13704	0.45961	2.71122	1.71501	2.46441	1.11545
700	-3.8468	-2.2312	-0.8208	-0.4561	0.76155	1.58456	1.43942	1.22782	0.23434
800	-3.7072	-1.5705	-1.3383	-0.6506	-0.3858	1.51126	2.2725	1.44395	0.60774
900	-2.1891	-1.489	-0.9355	-1.0028	-0.2355	1.92154	2.83866	1.90915	0.51776
1000	-2.0345	-0.8106	-0.4826	0.15774	0.29731	2.22648	3.55317	2.16055	0.96708
1100	-1.6858	-0.4413	-0.1354	0.08101	0.43076	2.75563	3.85085	2.62144	0.89396
1200	-2.2121	-1.2076	-0.4037	-0.7391	0.97073	2.46441	2.79632	2.81393	1.4779
1300	-1.6733	-1.1679	-0.6995	-0.2287	0.87768	2.06176	3.03109	3.45342	1.94567
1400	-2.0106	-1.3804	-0.0725	0.71139	1.1577	2.08954	3.05631	3.45396	2.35113
1500	-1.5596	-0.5055	-0.3127	0.68288	2.45498	3.00139	3.08609	3.72028	3.15968
1600	-1.3762	0.23634	-0.045	2.12462	2.80838	3.18759	3.00198	3.81945	2.36146
1700	-1.0551	0.01905	1.38193	2.17275	2.96958	3.93451	3.73209	4.12903	2.80402
1800	-0.572	0.3092	1.41658	2.03539	3.39838	3.77436	3.68438	3.71213	2.08907
1900	-0.1849	-0.0476	1.5204	2.32591	3.21346	3.6516	2.72928	3.30055	1.62608
2000	0.16519	0.33828	2.02744	2.72817	3.26042	3.29709	2.96617	3.27261	2.66945
2100	0.34081	0.82346	2.53702	2.87911	3.37334	3.1483	2.86631	2.95589	1.97513
2200	0.81398	1.22723	2.39665	2.8581	3.50132	2.19655	3.13659	2.84057	2.2198
2300	0.65649	1.01805	2.3801	2.99477	2.59519	2.43514	2.75657	2.38271	2.23851
2400	0.74901	1.02182	2.43102	2.8401	2.87586	2.9525	3.14146	2.50008	1.5266
2500	1.00828	0.83708	2.39173	2.60976	3.56346	3.87861	3.81021	3.25989	1.62857
2600	1.07197	1.08231	2.76657	3.40633	3.71647	3.98621	3.92762	3.05499	1.48039
2700	1.11551	1.07109	3.02353	3.637	3.65385	3.80356	3.9261	2.8321	1.52749
2800	1.21025	0.93762	3.06174	3.7164	3.46267	4.01556	3.96669	3.02515	0.37117
2900	1.12094	1.29584	3.24665	3.4755	3.4236	3.99064	4.04679	1.69701	-0.4203
3000	0.88755	1.33785	2.43555	3.60905	3.29288	4.0534	3.28851	0.71584	-0.1817
3100	0.71185	0.97913	2.4228	3.67577	3.29963	3.15996	2.53288	0.93967	0.46643
3200	0.39871	1.16507	2.88495	3.07602	2.72169	2.76061	1.97808	0.73047	0.51432
3300	0.46389	1.25379	2.78454	3.31991	2.21384	2.78508	2.02051	0.62146	0.93651
3400	0.69482	1.38133	3.11245	2.74581	2.18066	2.38277	1.69751	0.93739	1.2872
3500	0.66918	1.2096	3.30971	2.68741	2.00892	2.19023	1.65376	0.34366	0.30852
3600	1.08688	1.47506	3.45353	2.81814	2.09941	2.27342	1.62643	0.70001	0.4798
3700	1.07864	1.14987	3.03499	1.77702	1.96288	1.63867	0.31714	-0.0666	0.44846
3800	0.83184	1.8661	2.5603	1.83729	1.94383	1.33464	0.04854	0.0403	-0.0986
3900	0.91272	1.82352	2.20617	1.12494	1.54027	0.72036	-0.4528	0.16078	0.04346
4000	1.01373	1.80982	2.18394	0.88325	1.53499	0.5274	-0.4318	0.07062	0.02169
4100	1.0975	1.70274	1.89461	0.44888	1.29268	0.26058	-0.5461	0.73162	0.46001
4200	0.9918	1.50672	1.33384	0.33855	1.34323	-0.543	-1.2068	0.68879	-0.0386
4300	0.90592	0.97163	1.32214	0.92542	1.54099	-0.2439	-1.3644	0.57691	-0.2893
4400	0.89049	1.06499	1.1068	1.45999	1.32111	-0.5218	-1.4026	-0.0534	-0.3659
4500	0.45483	0.64371	1.0455	1.14086	0.60932	-0.8944	-1.3903	-0.0023	-0.5375
4600	0.85679	0.77854	1.45105	1.13791	0.22403	-0.9247	-1.3191	-0.1416	-0.1232
4700	0.52565	0.43865	1.11323	1.06753	0.55103	-1.3033	-1.4583	-0.5825	-0.16
4800	0.162	0.59208	1.24758	1.00152	0.57444	-1.4957	-2.0399	-0.633	0.29402
4900	0.14547	-0.0209	0.96675	0.54651	0.30638	-1.9839	-1.7696	-0.1636	0.15707
5000	0.16434	-0.0348	1.0442	0.62566	0.32478	-1.4273	-1.2509	-0.4154	-0.0446

Figure 4(a): 601066 Heatmap

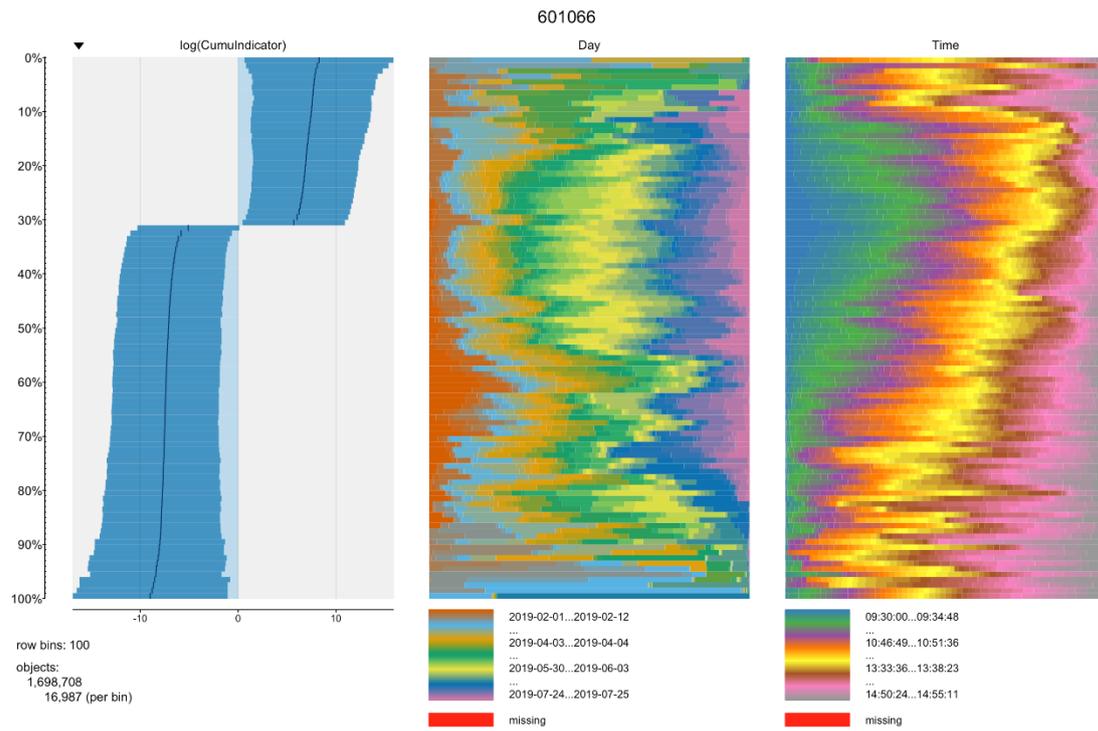


Figure 4(b): 601066 Table Plot

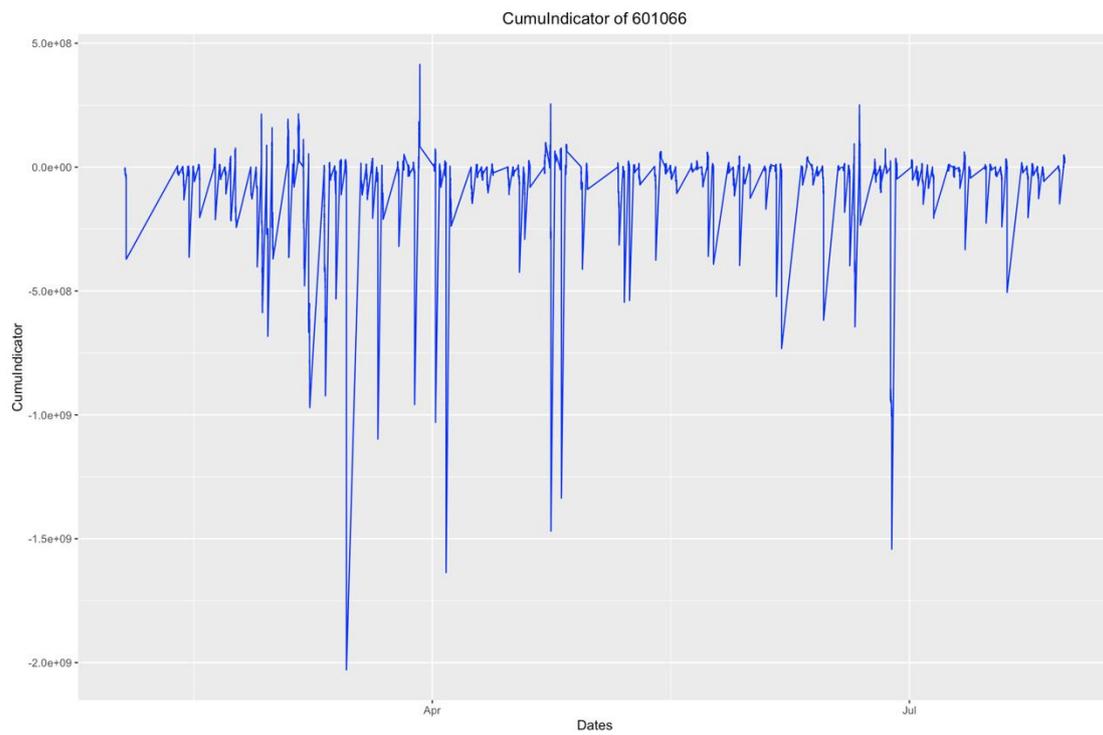


Figure 4(c): 601066 Cumuindicator

Sharpe EMA	STD								
	1.5	2	2.5	3	3.5	4	4.5	5	5.5
500	-15.108	-12.48	-9.9914	-7.6893	-7.136	-4.2624	-4.0213	-1.9329	-0.7663
600	-11.737	-9.8327	-6.7483	-5.6906	-3.7939	-2.114	-0.6959	-0.3198	-0.157
700	-9.852	-8.353	-6.315	-4.2089	-2.2048	-1.7191	-0.9354	-0.1417	0.5334
800	-7.7044	-6.0875	-3.8382	-2.1501	-2.0682	-0.5433	-0.5054	0.5361	1.07298
900	-6.9153	-4.8644	-3.0081	-1.0765	-1.5029	-0.408	0.44605	0.86414	1.79273
1000	-6.3064	-4.5811	-2.6283	-0.6525	-1.0625	0.28214	0.9196	1.18796	1.39012
1100	-5.6478	-3.9526	-1.7632	-0.402	0.30862	1.17421	0.60751	1.97931	2.17139
1200	-4.2814	-2.9351	-0.3637	-0.0145	1.45805	1.64543	1.42999	2.39754	1.49866
1300	-3.5548	-2.42	-0.3477	0.69184	1.76987	1.0867	1.42703	1.92462	0.28713
1400	-3.3573	-1.5706	-0.3377	1.05939	2.71	1.49534	1.0884	1.2887	-0.04
1500	-3.326	-1.3586	-0.5139	0.78755	2.57319	1.18539	0.82698	0.49612	-0.6362
1600	-2.7949	-0.9064	-0.3944	2.29407	2.10265	0.88374	0.84848	-0.4972	-0.2687
1700	-2.7696	-1.2892	0.31649	2.1177	2.57566	0.81646	0.68716	-0.2116	0.99801
1800	-2.3431	-1.2569	0.78837	2.09862	1.57324	0.63091	-1.1176	-1.2785	-0.3963
1900	-1.3968	-0.1518	1.04234	2.86885	2.24949	1.67587	0.16581	0.03	0.58544
2000	-0.959	0.06933	1.5076	2.51497	2.02066	1.7079	0.41664	0.28477	1.16319
2100	-0.4686	0.3387	1.58399	2.60436	2.6149	1.149	0.90201	0.66492	1.62898
2200	-0.1583	0.16219	1.54593	2.51515	3.04656	1.00005	1.51166	0.81659	1.0518
2300	0.21187	0.28802	1.9067	2.52484	2.71859	1.68995	1.39331	0.26723	0.75277
2400	0.35221	0.35688	1.64544	3.02939	2.40629	1.16911	0.72582	0.17863	0.42788
2500	0.05109	0.4205	1.66978	2.68572	2.5759	0.83529	0.04354	0.13089	0.40527
2600	0.18608	0.30757	1.76142	2.23053	2.5851	-0.2233	-0.1002	0.19095	0.30091
2700	0.20485	0.45506	1.40133	2.31249	2.21065	-0.2923	0.47145	0.22666	0.03517
2800	-0.1674	0.30411	0.89216	2.14399	1.73377	-0.2988	0.51307	0.36743	0.15419
2900	0.01713	0.49628	1.30631	1.80383	1.74722	-0.1401	0.41222	0.25195	0.3631
3000	-0.0357	0.45319	0.84051	1.50663	1.9796	0.27538	0.24846	0.29573	0.45874
3100	-0.1842	0.19963	0.65254	1.5466	1.46687	0.25227	0.00981	0.22911	1.20732
3200	-0.1634	0.47271	1.01265	2.08523	1.76325	-0.062	-0.0793	0.5774	0.89579
3300	-0.2099	0.41973	1.33467	1.87868	2.69757	0.45883	0.14757	0.78655	1.46769
3400	-0.2323	0.80247	1.34159	1.51216	2.26056	0.45189	0.35963	0.86308	1.42717
3500	0.25706	1.27907	1.45957	2.16758	1.7034	0.61874	0.4245	0.82349	1.43657
3600	0.27004	1.38172	1.42142	1.68564	1.31322	-0.3836	-0.0554	0.37501	0.78633
3700	0.2374	1.75056	1.57093	1.31129	1.48181	-0.3783	-0.1948	1.13223	0.81336
3800	0.13049	1.7173	1.27591	0.83088	1.36091	-0.6817	-0.4821	0.73766	0.65937
3900	0.148	1.38974	1.32906	0.49469	1.62687	-1.2744	0.2799	0.67693	0.35784
4000	-0.0593	1.26047	1.45578	0.14826	1.04424	-1.3642	0.06969	0.30247	0.40431
4100	0.16827	1.14041	1.15006	1.20522	0.73425	-0.701	-0.1807	0.06785	-0.0283
4200	0.01254	1.21919	1.33591	1.16222	0.44686	-0.6104	-0.8887	-0.0421	0.51653
4300	-0.422	1.00001	1.04813	0.83267	0.45528	-0.5968	-0.4005	-0.2142	0.53316
4400	-0.5498	0.90101	1.07183	0.34775	-0.0754	-1.0033	-0.3446	0.5334	0.46307
4500	-0.2117	1.09696	1.10061	0.05907	0.08839	-0.8375	-0.3469	0.70405	0.1639
4600	-0.7117	1.21108	0.9635	-0.0421	-0.4782	-0.5009	0.16998	0.64977	0.03656
4700	-0.756	1.26488	0.83057	0.03397	-0.5171	-0.7094	-0.2612	0.62266	0.18133
4800	-0.573	1.11003	0.39528	-0.8061	-0.572	-0.5937	-0.2401	0.37239	0.18333
4900	-0.6147	1.0366	0.50434	-0.3817	-0.9786	-0.8832	-0.9605	0.31752	0.20498
5000	-0.2269	0.91381	0.20601	-0.6173	-1.3128	-1.0599	-0.8032	0.23282	-0.0033

Figure 5(a): 601155 Heatmap

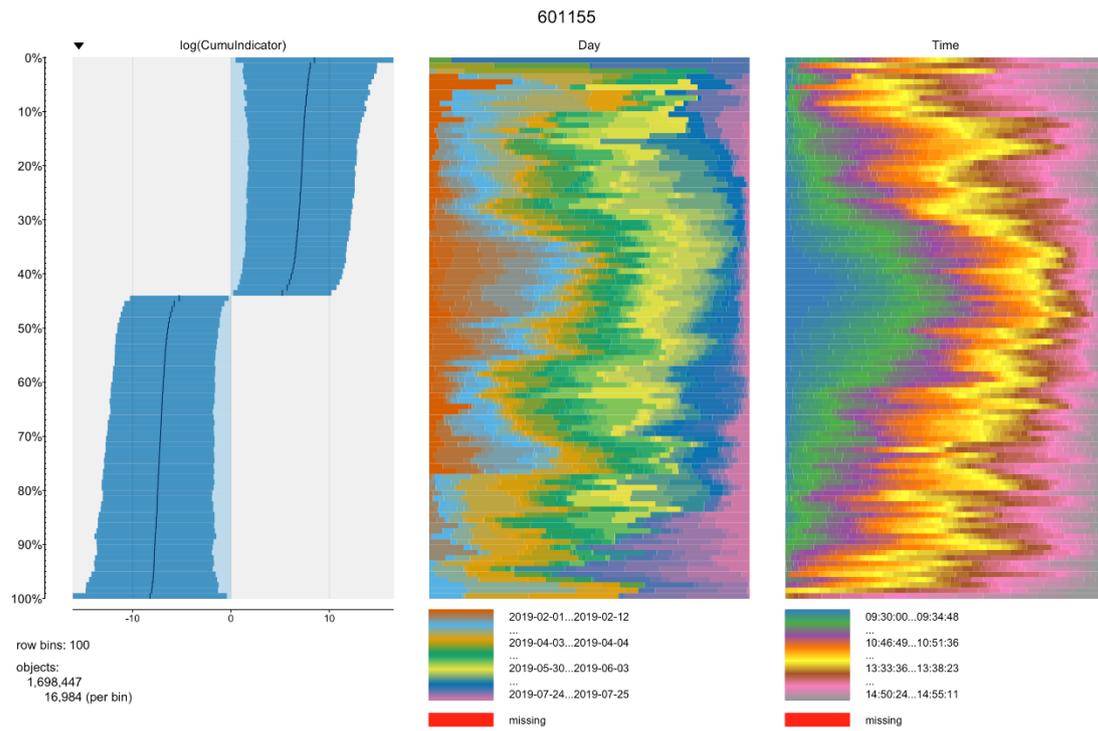


Figure 5(b):601155 Table Plot

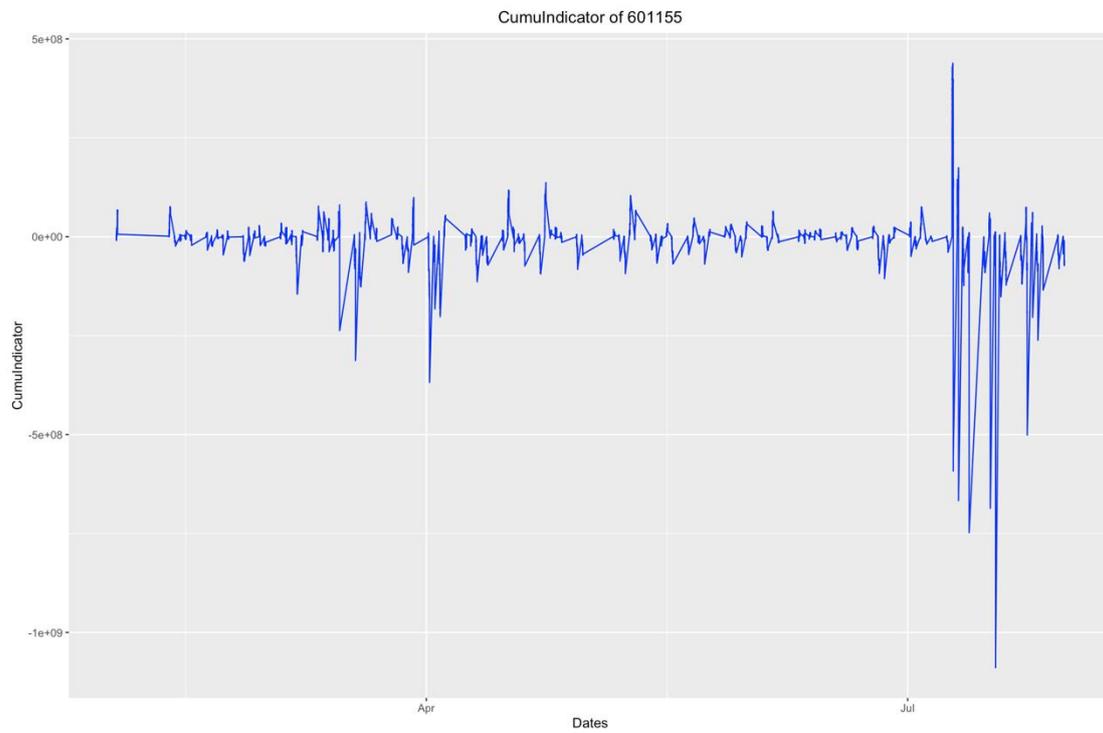


Figure 5(c): 601155 Cumuindicator