Order Imbalance Based Trading Strategy

IEOR4733 Group 8

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Abstract

This paper studied the high frequency trading strategy based on the order imbalance. First, we introduced order imbalance indicators and build the basic and improved pricing model. Then with the high frequency trading data on nickel, rubber, rebar, copper and aluminum from Shanghai Futures Exchange, we studied on the statistical properties of the order imbalance indicators and models, and get the significant results, showing that the order imbalance indicators do have some explaining and predicating power over the future price move. The significant results provide us the solid foundation on developing a trading strategy that is mainly based on the order imbalance data from the market. In addition, we executed the strategy and evaluated the strategy performance. Comparing the performance results on all five kinds (nickel, rubber, rebar, copper, and aluminum) of metal futures, we found that there exists obvious difference between the cumulative profits of different futures. Moreover, when the volatility of a metal futures is high, the daily profits of this futures tend to fluctuate to a larger range. Eventually, we optimized our parameters to make further improvement over the model and increased the profitability of the trading strategy.

Keywords: order imbalance, metal futures, high frequency trading strategy

I. Background

Nowadays, the high frequency trading is gradually becoming an important topic in the finance field. With the assists from computer, it is now feasible to analyze massive data and develop trading algorithm to make high-speed trade decisions.

The indicators generated from available data are very important to develop an effective trading model. Things like current order volumes of both trade sides can contain some valuable implicit information. If we take the difference of order volumes from two side, the imbalance of volumes can be a signal to reflect the current market, and thus, we think it is worthwhile to explore the trading model and strategy based on order imbalance.

II. Model Introduction

1. Volume Order Imbalance (VOI)

A natural consideration would be just the difference between the volume of bid orders and the volume of ask orders, and we can give a formal name to it as: “Volume Order Imbalance (VOI)”.

To make our research in a conservative way, according to Shen [5], the math expression of Volume Order Imbalance (VOI) can be defined as: $\mathrm{VOI}_t = \delta V_t^B - \delta V_t^A$

Where $$.\delta V_t^B = \begin{cases} 0, & P_t^B - P_{t-1}^B < 0 \\ V_t^B - V_{t-1}^B, & P_t^B - P_{t-1}^B = 0 \\ V_t^B, & P_t^B - P_{t-1}^B > 0 \end{cases}$$

$$\delta V_t^A = \begin{cases} 0, & P_t^A - P_{t-1}^A < 0 \\ V_t^A - V_{t-1}^A, & P_t^A - P_{t-1}^A = 0 \\ V_t^A, & P_t^A - P_{t-1}^A > 0 \end{cases}$$

Here, V_t^B and V_t^A represent bid volume and the ask volume at time t. The P_t^B and P_t^A here represent the bid price and ask price at time t.

2. Basic Model

The basic model includes historical VOI as the independent variables.

The basic model is as follow:

$$\overline{\Delta M_{t,k}} = \beta_c + \sum_{j=0}^{L} \beta_j \mathrm{VOI}_{t-j} + \varepsilon_t$$

Where $\overline{\Delta M_{t,k}} = \frac{1}{k}\sum_{j=1}^{k} M_{t+j} - M_t$, which is the k periods average move of mid-price.

VOI_{t-j}: The jth lag of the Volume Order Imbalance

3. Order Imbalance Ratio (OIR)

One problem about Volume Order Imbalance (VOI) is that it only reflects the absolute difference. If both sides increased a lot in volume, we may want to know the proportion of outnumbered volume. To adjust this, according to Shen [5], we introduce a new indicator “Order Imbalance Ratio”.

The Order Imbalance Ratio (OIR) is:

$$\rho_t = \frac{V_t^B - V_t^A}{V_t^B + V_t^A}$$

We can see that the added denominator is the sum of total volume. It can adjust the effects brought by the scale of volumes.

4. Mid Price Basis (MPB)

In addition, we introduce the indicator Mid Price Basis (MPB). Let $\mathrm{R_t}$ denote MPB at period (t-1, t), according to Shen [5], we can define the math expression of $\mathrm{R_t}$ (MPB) as:

$$\mathrm{R_t} = \overline{\mathrm{TP_t}} - \overline{\mathrm{MP_t}}$$

Where

$$\overline{TP}_t:\ Aver.\ transaction\ price\ in\ (t-1, t]$$
$$\overline{MP}_t:\ Aver.\ mid\ price\ in\ (t-1, t]$$

$\mathrm{R_t}$ can be the important indicator for the price change. If $\mathrm{R_t}$ is a large positive value, then we can deduce that the mean price of actual transactions is very close to the ask price, meaning that transactions are mainly driven by buyers, and similarly, negative value indicates that sellers are driving transactions.

5. The Improved Model

Now we construct the improved model. It includes all indicators we've introduced (VOI, OIR and MPB), and is the linear combination of these indicator values. The expression of the new model:

$$\overline{\Delta M_{t,k}} = \beta_0 + \sum_{j=0}^{L} \beta_{VOI,j} \frac{VOI_{t-j}}{S_t} + \sum_{j=0}^{L} \beta_{\rho,j} \frac{\rho_{t-j}}{S_t} + \beta_R \frac{R_t}{S_t} + \epsilon_t$$

Where $\overline{\Delta \mathrm{M_{t,k}}} = \frac{1}{\mathrm{k}} \sum_{\mathrm{j=1}}^{\mathrm{k}} \mathrm{M_{t+j}} - \mathrm{M_t}$, which is the k periods average move of mid-price.

VOI_{t-j}: The jth lag of the Volume Order Imbalance

ρ_{t-j}: The kth-order lag of Order Imbalance Ratio.

R_t: The Mid Price Basis at time t

S_t: The bid-ask spread at time t.

III. Data Introduction

As for the data, it's from Shanghai future exchange. The date range is between March 1st 2017 to March 31st 2017. The time interval between each record is 500 milliseconds. It includes 5 types of commodities, which represents different contracts. Additional on the original result, we add one more column called 'second of day'. It is the numerical version of the trading time. Our strategy is based on one-day data. Therefore, we randomly picked 20170301 as our dataset and use all of the dataset (23 days) to do back test.

IV. Statistical Analysis

1. Goal: Check whether VOI and OIR share the same statistical property

Based on the definition, both VOI and OIR are used to measure order imbalance. That's why they should share the same statistical property. Here, we calculate autocorrelation to see whether this assumption is met.

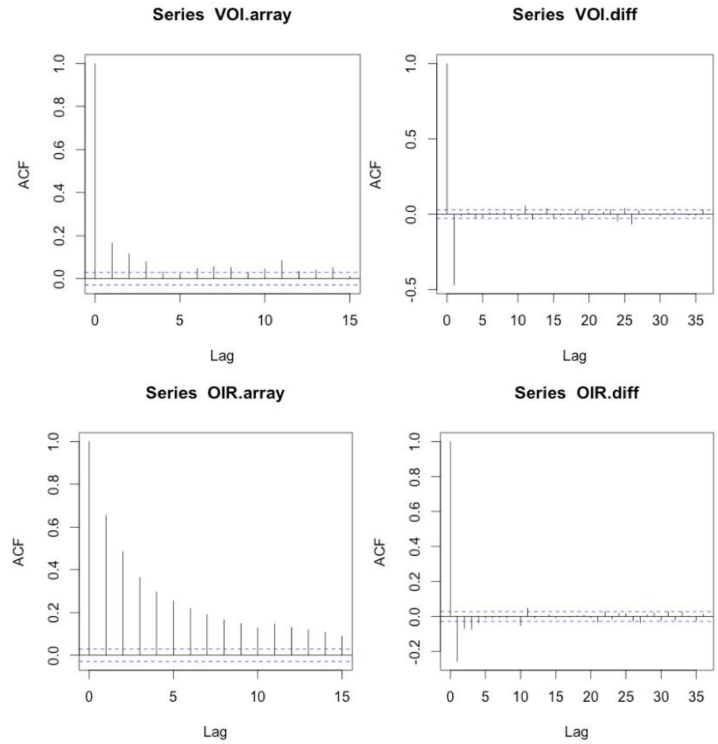

Figure 1. Autocorrelations

Since both autocorrelation charts have the same signs and trends. We could conclude that they have the same statistical property.

Another interesting finding is that there are several strong positive ACF among the first several periods and it decreased along the time. The reason is traders tend to split their orders across several periods.

2. Goal: Check whether MPB has mean reversion

We use MPB to indicates whether the market is a buy side or sell side. Therefore, we need MPB to have mean reversion property. To test this, we calculate the VR across all the lags. Based on the result, we could see that all the VRs are below 1 which indicates that MPB has mean reversion.

1. Goal: Check whether the data is stationary

If the data is not stationary, then the market has structural changes. In this case, we could not use previous day's linear model to predict future trading signal. Therefore, we must test the data is stationary. Based on the line charts, although there are some points have high volatility, most of them are fluctuated within a certain level. Furthermore, both of the ADF test and

KPSS test show the result that our data is stationary. Therefore, we could apply our strategy on every trading day.

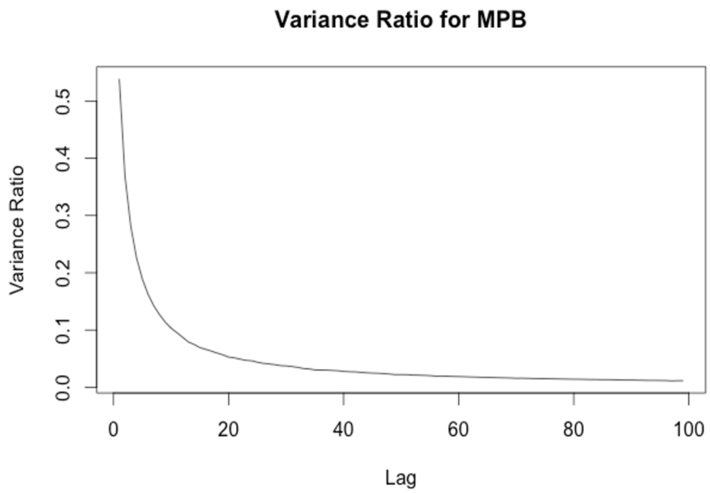

Figure 2. Variance Ratio for MPB

2. Analysis on Linear Regression Models

1) Basic model

We first fit a basic linear regression model to the trade data of Nickel contract on March 1st, 2017. From the result we can see that the instantaneous VOI and VOI up to lag three are significant, so that we conclude that order imbalance contributes to the prediction of future price movement. The R^2 of this model is 4.6%. Even though it is quite small, it is still consistent with the result conducted on NASQDA equity data in our reference paper.

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.039356   0.038622   1.019 0.308212
VOI.t0      0.097196   0.002485  39.108  < 2e-16 ***
VOI.t1      0.043912   0.002496  17.590  < 2e-16 ***
VOI.t2      0.021829   0.002504   8.719  < 2e-16 ***
VOI.t3      0.008512   0.002503   3.401 0.000672 ***
VOI.t4      0.002356   0.002496   0.944 0.345131
VOI.t5      0.002151   0.002484   0.866 0.386659
```

Table 1. Linear Regression Summary for Basic Model

2) Improved model

To improve model performance and capture more variability in middle price movements, we try to incorporate other variables such as MPB and OIR into our model. The R^2 of the model is 10.9%, which has increased 6% when compared to the previous model. Based on the model output, we can see that VOI up to lag three are still significant, which is consistent with the previous model output. MPB and the majority of OIR are significant under different significant levels.

```
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.08062    0.03738   2.157 0.031012 *
VOI.t0        0.85545    0.02807  30.474  < 2e-16 ***
VOI.t1        0.52780    0.02771  19.049  < 2e-16 ***
VOI.t2        0.26181    0.02706   9.676  < 2e-16 ***
VOI.t3        0.15239    0.02909   5.238 1.63e-07 ***
VOI.t4        0.05284    0.02828   1.868 0.061764 .
VOI.t5        0.05856    0.02931   1.998 0.045774 *
OIR.t0       50.63461    0.93395  54.215  < 2e-16 ***
OIR.t1      -16.25035    1.06583 -15.247  < 2e-16 ***
OIR.t2       -4.62786    1.07596  -4.301 1.70e-05 ***
OIR.t3       -0.15072    1.07103  -0.141 0.888086
OIR.t4       -2.57533    1.06275  -2.423 0.015385 *
OIR.t5       -3.37408    0.94787  -3.560 0.000372 ***
MPB           0.25304    0.02714   9.323  < 2e-16 ***
```

Table 2. Linear Regression Summary for Improved Model

3) Basic model on all commodities

The above result only base on one-day trade data on nickel contract. In order to see the overall effect of these models on different commodities, we fit each of these two models using the whole data set. We come up with 115 basic linear regression models and 115 improved linear regressions. Then we calculate the percentage of variable when the coefficient of them are positive and significant. Based on the output, VOI with no lag and VOI with lag 1 indicates positive relationship for all commodities with 100% certainty. However, VOI with lag two and lag three only perform well on selected commodities such as nickel and rebar, while the performance on copper is quite bad.

	NI	RU	RB	CU	AL
Intercept	0.04%	0.00%	0.04%	0.04%	0.09%
VOI_t0	100.00%	100.00%	100.00%	100.00%	100.00%
VOI_t1	100.00%	100.00%	100.00%	100.00%	100.00%
VOI_t2	100.00%	82.61%	100.00%	39.13%	52.17%
VOI_t3	78.26%	17.39%	60.87%	8.70%	0.00%
VOI_t4	30.43%	4.35%	30.43%	4.35%	0.00%
VOI_t5	4.35%	4.35%	30.43%	0.00%	4.35%

Table 3. Significant Percentage of VOI for 5 Metals (Basic Model)

4) Improved model on all commodities

We did the same thing as mentioned above using the improved linear regression model. In the output, VOI up to lag two, instantaneous OIR and MPB indicates positive relationship with the response variable. One thing for us to think about is the percentage of OIR with lag 1 to lag 5 are all zero. So that we would like to evaluate the performance of these five variables separately. Using the same methodology, we calculate the percentage for these variables when their coefficients are negative but significant. We found that the smallest percentage here is 65%, which can greatly explain why we have zero percentage in the previous step. Based on the analysis above, the improved model is better than the basic model in terms of predicting their middle price movement.

	NI	RU	RB	CU	AL
Intercept	13.79%	8.70%	4.35%	26.09%	17.09%
VOI_t0	100.00%	91.39%	86.96%	100.00%	100.00%
VOI_t1	100.00%	100.00%	91.65%	100.00%	100.00%
VOI_t2	100.00%	95.65%	91.30%	73.91%	82.61%

VOI_t3	86.96%	43.48%	91.30%	17.39%	26.09%
VOI_t4	52.17%	8.70%	82.61%	8.70%	13.04%
VOI_t5	30.43%	4.35%	69.57%	8.70%	13.04%
OIR_t0	100.00%	100.00%	100.00%	100.00%	100.00%
OIR_t1	0.00%	0.00%	0.00%	0.00%	0.00%
OIR_t2	0.00%	0.00%	0.00%	0.00%	0.00%
OIR_t3	0.00%	0.00%	0.00%	0.00%	0.00%
OIR_t4	0.00%	0.00%	0.00%	0.00%	0.00%
OIR_t5	0.00%	0.00%	0.00%	0.00%	0.00%
MPB	100.00%	91.30%	86.96%	100.00%	100.00%

Table 4. Significant Percentage of Indicators for 5 Metals (Improved Model)

	NI	RU	RB	CU	AL
OIR_t1	100.00%	100.00%	100.00%	100.00%	100.00%
OIR_t2	100.00%	100.00%	100.00%	86.96%	100.00%
OIR_t3	82.61%	78.26%	91.30%	73.91%	100.00%
OIR_t4	65.22%	69.57%	95.65%	78.26%	95.65%
OIR_t5	82.61%	86.96%	100.00%	91.30%	100.00%

Table 5. Significant Percentage of Negative OIR for 5 Metals (Improved Model)

Finally, we conclude that instantaneous VOI and VOI with lag one to lag three indicate positive relationship with the response variable. OIR with all lags are significant for all commodities, in which the instantaneous OIR indicates positive relationship with the response variable, while the rest of them indicate negative relationship. We then decide to use both the basic and improved model as our trade model so that we can compare their performances.

V. Backtest

1. Strategy

In this part, we used backtest method to analyze the effectiveness our model. In order to make things simple, we made some assumptions. 1. We can always sell at the bid price and buy at the ask price. 2. There is no time lag from getting the data to executing the trade 3. The cost is 0.025% for every trade. 4. The maximum position we can hold is ±1 contract, and we can only trade whole contracts.

We invest in future contracts with the highest trading volume among each kind of commodity futures. Therefore, we traded at futures which expiration month is May 2017. Our trading time period starts from 2 minutes after the market opens and 2 minutes before the market closes. This is because, at the beginning and the end of the market, the order volume is volatile. Prediction based on this kind of data is not reliable.

We select K=5 as the parameter of $\overline{\Delta M_{t,k}}$, and selected L=5 as time lag of VOI and OIR. Starting from day t0, we used data from day t-1 and data from day t-2 to regress the model respectively.

In this way we get can get coefficient $\beta_{i,t-1}$ and $\beta_{i,t-2}$ for each explanatory variable in day t-1 and day t-2. Then we take the average of $\beta_{i,t-1}$ and $\beta_{i,t-2}$ to get $\bar{\beta}_{i,t0}$. For the special case, if day t-1 is the first day which means that we do not have data for $\beta_{i,t-2}$, so instead of taking the average we will just let $\beta_{i,t-1}$= $\bar{\beta}_{i,t0}$. Therefore, we can calculate predicted $\overline{\Delta M_{t,k}}$ at day t0 every 500 milliseconds by using the latest variables (VOI for basic mode and VOI, OIR and MPV for improved model).

If $\overline{\Delta M_{t,k}}$ is smaller than negative minimum tick size then we will adjust our position to -1. If $\Delta M_{t,k}$ is larger than minimum tick size then we will adjust our position to +1. Otherwise the predicted price change $\overline{\Delta M_{t,k}}$ is too small to change our position, so we simply keep the current position. We will close our position 2 minutes before the market closes because we do not want to bear additional risk when the market is closed.

2. Result

Type	Daily Avg. Profit	Std.	% of Days Pos Profit	Daily Avg. Num of Transactions	Initial Amount of Money	Daily Avg. Return
Basic Model						
Nickel	621	1264	68%	140	100,000.00	0.6%
Rubber	2847	3754	73%	58	200,000.00	1.4%
Rebar	-105	405	32%	11	40,000.00	-0.3%
Copper	-543	1659	23%	20	250,000.00	-0.2%
Aluminum	-157	437	27%	13	80,000.00	-0.2%
Improved Model						
Nickel	1474	1624	77%	241	100,000.00	1.5%
Rubber	2865	5003	64%	78	200,000.00	1.4%
Rebar	103	557	45%	21	40,000.00	0.3%
Copper	-685	1775	32%	19	250,000.00	-0.3%
Aluminum	-220	467	36%	13	80,000.00	-0.3%

Table 6. Summary of Backtest Results

Table 6. is our backtest result. At first, we can find that Nickel and Rubber have better performance than rebar, copper, and aluminum in both models. Secondly, we can see that improved model has better performance than the basic model. Profit of every contract has increased when switching from basic model to the improved model. In addition, profit of Rebar becomes positive if we use the improved model instead of using basic model. In order to calculate daily average return, we select initial amount of money that we can buy only 1 share of futures. We can find that Nickel has the highest daily average return which is 1.5% and 1.4% if we use improved model.

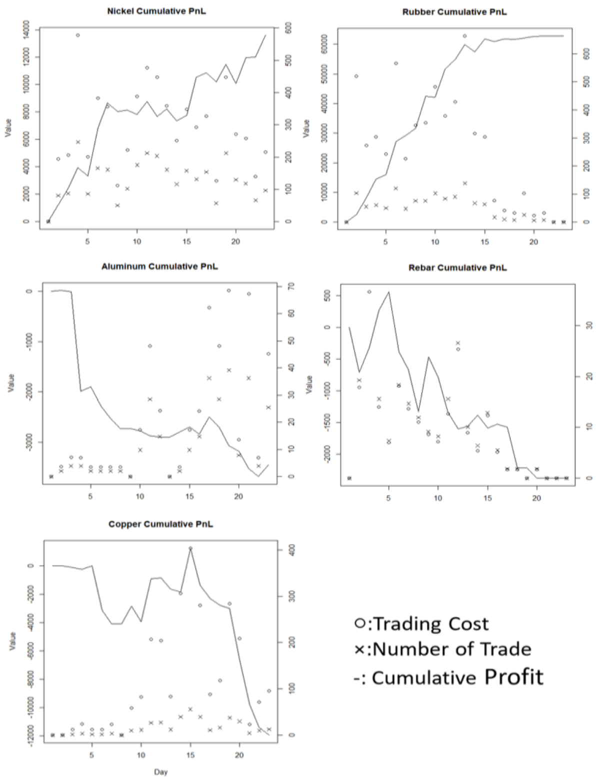

Figure 3. Trading Cost, Number of Trade and Cumulative Profit of Basic Model

Figure 4. Trading Cost, Number of Trade and Cumulative Profit of Improved Model

From Figure 3 and Figure 4, we can find that number of trade varies from days to days. For example, the number of trade of aluminum is large at the end of the month, while the number of trade of rebar is high at the beginning of the month. We can also find that there is no trade in some days. For example, when we are using the basic model we do not trade rebar and rubber at the end of the month.

3. Relationship Between Profit and Number of Transactions

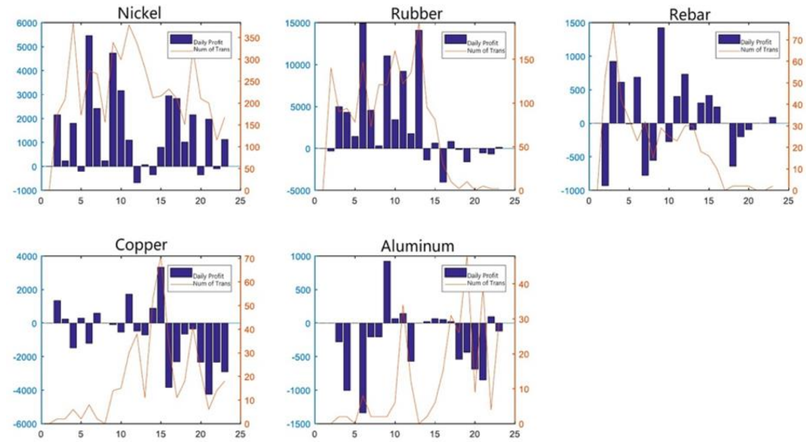

Figure 5. Number of Transactions and Daily Profit

To have a deeper understanding of the performance of our strategy, we look the relationship between number of transactions and daily profit. And the result is shown in figure 5.

The first graph shows the relationship for Nickel. The daily profit in the chosen period days are mostly positive, which is a good signal in evaluating the performance of our strategy. And the graph shows that in general, the number of transactions is positively correlated with the daily profit. So our strategy has a good performance in this period.

In the second graph, for Rubber, it is a little different. Usually the more volatility, the more number of transactions will be triggered because the absolute value of the independent variable increases, which may lead to an increase in the absolute value of the dependent variable (also depend on the size and direction of the regression coefficient. However, when the direction and magnitude of the regression coefficient do not change a lot, the absolute value of the explanatory variable corresponding to the larger regression coefficient increases, and the price is more likely to change according to the direction of its variation). If the number of trades increases, the profit drops, which shows that during this period, our strategy inefficient. However, the number of transactions is not the same as the visual imagination. We can see from the Figure 5 that the number of transactions of rubber dropped significantly since day 16, which almost has the same trend as the decrease of the cumulative monthly profit, and it may happen Systematic changes (external shocks, such as changes in national policies) have led to a large change in the sign and magnitude of the regression coefficients, thereby reducing the number of transactions before the volatility increases.

For Rebar, with fewer trades, daily profit moves from a negative value toward zero, which means the loss is reduced, indicating that the strategy lapped on the rebar after the 18th day. At the same time in the previous period also appeared in the number of transactions and profits deviate from the phenomenon, indicating that the strategy on the performance of the species is not stable

Since the 17th trading day, Copper experienced a significant decline in the number of trades and a sharp loss from there. It is possible that copper will take a long time (the price of the model will always be positive or negative and the trading system will be long Time did not open), but no corresponding profits, but a huge loss, indicating that the strategy lapsed at this time.

In combination with volatility, it can be seen that Aluminum trades more in the case of low volatility, which is exactly the same phenomenon as copper.

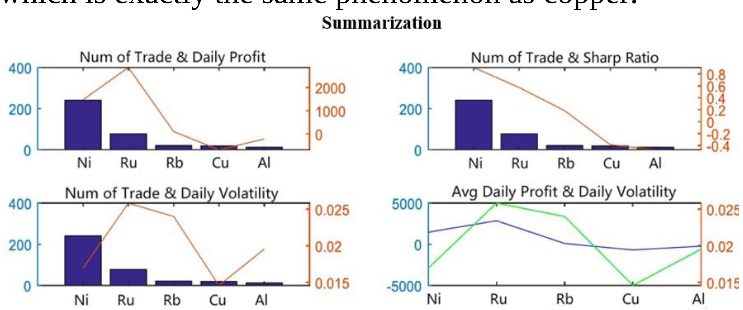

Figure 6. Summarization of the Relationships

Why the difference in profit among varieties exist? Through observation, we noticed that one possible reason is the average daily number of strategies traded on that varies. As can be seen from Figure 6, except for nickel, the ranks of average number of daily transactions and the average daily profit are the same in general, which can be used as a direction for deeper research. Although there is not a strong correlation between the number of transactions and the daily volatility from Figure 6, the daily average number of transactions of the strategy is related to the daily average volatility. The reason for the unclear relationship in the figure above may be that during the period that we chose, some effect from outside, like the chance of government policy, exists, which may change the pattern of number of transactions. Based on the definition of imbalanced orders, the larger of daily average volatility, the stronger imbalanced order signal will be sent, which will increase the number of transactions. So intuitively, number of transactions is often positively correlated with daily volatility. And in the graph we can see that the average daily volatility is quite different. After different times of trading, different daily average profits are generated, which can be observed from the correlation between daily average profit and daily volatility in Figure 6.

4. Relationship between profits and price volatility

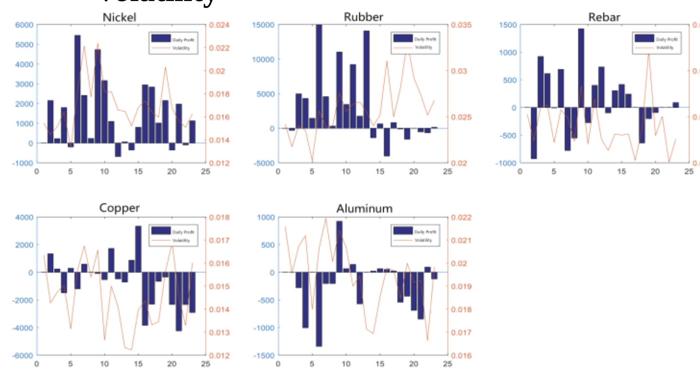

Figure 7. Price Volatility and Daily Profit

We further explore the relationship between price volatilities of all five futures varieties and profits under our improved model.

When looking at the right vertical axis, we find that compare with Copper and Aluminum, the first three varieties, Nickel Rubber and Rebar have higher volatility. Also they have higher profits than Copper and Aluminum. Hence, intuitively, we can say that daily profit has a positive relationship with price volatility. The larger the volatility, the larger the daily profits. Then we can conclude that the strategy is likely to has better effect on active market when the volatility is large enough. We can apply this property and take volatility as a timing index. When the volatility is larger than the threshold value, we employ this strategy to implement trading orders. When the volatility is not large enough, maybe our strategy will not make great profits.

If the positive correlation between profits and price volatility should be under the condition that the transaction times is large?

	Nickel	Rubber	Rebar	Copper	Aluminum
22-day correlation coefficient	0.57	-0.17	0.33	-0.1	-0.15
Former-11-day correlation coefficient	0.59	0.6	0.68	0.01	-0.08
Later-11-day correlation coefficient	0.45	-0.36	-0.22	-0.33	-0.37
Former-11-day profits/later-11-day profits	1.68	7.54	128.39	-0.03	1.04
Former-11-day volatility/later-11-day volatility	1.06	0.9	1.05	1.05	1.08
Former-11-day traction times/later-11-day transaction times	1.29	2.99	4.67	0.4	0.33

Table 7. Transaction Summaries for 5 Metals

We calculated the correlation coefficient between profits and price volatility in five varieties. We further truncated the data into two time periods, the first 11 days and later 11 days, collecting the ratio of these time periods with respect to correlation coefficient, profits, volatility, and transaction times. From this table, we can see that according to Nickel, Rubber and Rebar, price volatility has a positive correlation with daily profit only when the transaction times are large enough (former 11 days for these three varieties). If the transaction times are small, like Column and Aluminum, the relation between daily profit and volatility changes, even reverses to negative values.

VI. Parameter optimization

The parameters we used in the strategy include the forecast period window k, the lag order L of VOI and OIR, and the calculation mechanism of the regression parameters inside the strategy. In the following part, we will focus on Nickel and do optimization on its prediction window k and lag order L.

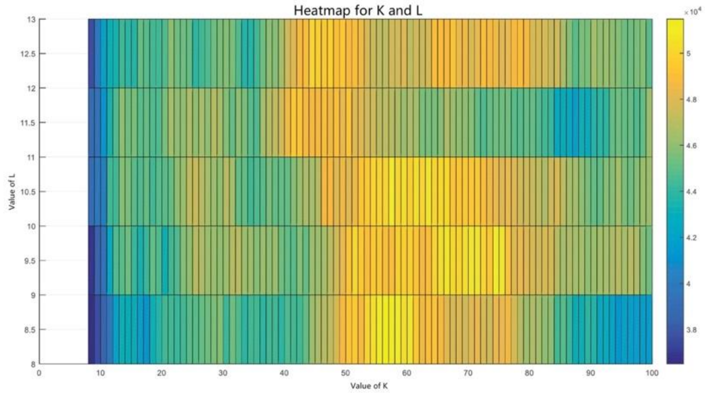

Figure 8 Heatmap for K and L

The cumulative profit heat map above is obtained by using 2-day simple moving weighted averaging when the regression parameters are brought into the strategy backtest (as defined in Equation 6.1). We can see from Figure 12 that when k = 57 and L = 8, the accumulated profit reaches the maximum, so for the nickel contract due in May 2017, the forecast window should be set to 57 and the lag order should be set to 8. A possible reason is that as the prediction window k increases, the volatility of the explained variable will become small, and the strategy will become more stable, so that the number of retractions will be reduced and the retracement rate will be reduced during the back testing, and the profit can also increase.. However, it should be noted that the parameters often have a platform period. During the platform period, the cumulative profits may be stable at a certain level, not rapidly increase or decrease. After the platform period, the accumulated profits will fall. This is especially true for the forecast window k, since fluctuations in the average median price decrease when k is large, since volatility in a Median price does not actually affect its fundamentals and may lead to inaccuracy predictions and also the decrease of profit.

We set k from 5 to 90, L from 8 to 13 and do experiments to observe the corresponding changes in monthly cumulative profits. We can see from the figure that regardless of the value L takes between 8 and 13 and K takes between 5 and 50, the monthly cumulative profit grows rapidly with increasing k; when K takes a value between 50 and 80, monthly cumulative profit is stable in the platform period corresponding to the monthly cumulative profit of 50,000 or so; in K to 80 to 100, the monthly cumulative profit began to decline, and our forecast results are basically the same. We expect that the monthly cumulative profits will continue to decrease as k increases, since the change of a single middle price does not have an actual impact on the overall average mid-price movement when k is large, resulting in a forecast profit insensitive compared with the instruction imbalanced sequence change, resulting in long positions and the decline in cumulative profit.

Next, instead of using only the regression parameters from the previous day, we also consider the weighted moving average of the p-day parameters:

$$\hat{\beta}_i^{(d)} = \sum_{j=1}^{p} w_j \beta_i^{(d-j)}, \sum_{j=1}^{p} w_j = 1 \tag{6.1}$$

One way to estimate the weight w_j is to use AR (p) model when verifying the autocorrelation between $\beta_{i\,(d)}$ and $\beta_{i(d-j)}$. Another method is to use a simple moving average of parameters of previous p day. We only consider second method below. In this optimization, p takes values from 1 to 22 (since there are only 23 trading days, we can only use up to the first 22 trading days).

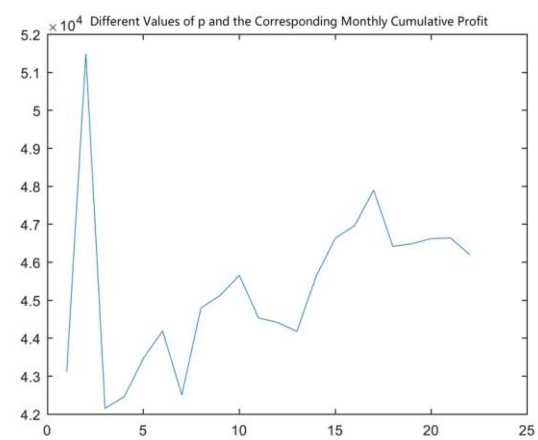

Figure 9 Change of p Value and Corresponding Cumulative Profit (k = 57, L = 8)

We set k = 57, L = 8 and adjust p. As can be seen from the figure above, when p = 2, the cumulative profit is the largest, so the optimal parameter is p = 2 (since p= 2 reaches the maximum when k = 57 and L = 8; under the condition of p = 2, k = 57 and L = 8, we get the maximum profit. Though this is not the sufficient condition of local maximum, it is also necessary). The accumulated profits continue to rise when the value of p lies between 3 and 22, but they still do not exceed the previous values. But it is foreseeable that when changing the values of k and L, the optimal value of p may change, so for each set of parameters k and L, we need to find the value of p again.

VII. Conclusion

1. Original paper is based on data of China Financial Futures Exchange (CFFEX) CSI 300 Index Futures (IF). But we test and find that there also exists order imbalance in Chinese commodity futures market.
2. Our models can be used to predict future price change. Improved model has higher daily average revenue. Daily average profit of rubber becomes positive after switching to improved model. Hence, when conducting the trading strategy, we prefer to use the improved model.
3. But the strategy is not efficient for all the varieties. Nickel and Rubber have higher profits under strategy, compared with copper and aluminum. By analyzing number of transactions as well as the coefficient between price volatility and strategy profits, we find that only when the volatility is large enough, and making a lot of transactions, we can make stationary profit.

VIII. Prospect

Here we raise some shortcomings of our model and come up with potential improvements.

1. The sample data we used is not large enough. We only conclude five commodities with one-month-long data. It is better to test on at least one year to get more stable results. And we can explore the general applicability under other futures varieties or other derivatives.
2. This paper use OLS (ordinary least squares) regression, and the R square is not large enough. We can consider change it into logit regression and probit regression, which may come up with better regression results.
3. This strategy defines maximum holding between +1 and -1 for convenience of controlling variables. But to have more realistic results, we can cancel this limit and make further exploration about optimal positions (like employing the methods of Kelly formula), and see how positions may cause differences to our strategy.

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