Project Title	Nowcasting Forward Freight Agreement with IODEX Through VAR, Rolling VAR and DF
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Itemized workload	
Data collection	20 hours
Literature review	20 hours
Programming	40 hours
Market Convention Exploration	28 hours
Total work load	108 hours

Original contribution	This project has the following original contributions:
(1)	Conducted the study on 5TC which is a new standard according to Baltic Exchange since 2014
(2)	Designed a tradable derivative (named Return Index) of Forward Freight Agreement to forecast
(3)	Tested Granger causality between log difference of IODEX and Return Index instead of T&Y
(4)	Compared performance of static VAR, rolling VAR and Dynamic Factor Model with Kalman filter

NOWCASTING FORWARD FREIGHT AGREEMENT WITH PLATTS IRON ORE INDEX THROUGH VAR, ROLLING VAR AND DYNAMIC FACTOR MODEL

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ABSTRACT

The aim of this study is to investigate the relationship between Return Index derived from Capesize 5 Routes Time Charter Average (5TC) Forward Freight Agreement (FFA) and IODEX. Price of major bulk is expected to have an influence on bulk carriers demand and consequently affect the forward price of freight rate reflected through FFA. In order to analyse the lead-lag relationship in a certain period between Capesize 5TC FFA and Platts Iron Ore Index (IODEX), empirical studies including cointegration rank test, Granger Causality test, Impulse Response analysis are conducted. To investigate if dynamic models can do better 1-step-ahead forecast, strategies using static and rolling Vector Autoregression (VAR) as well as Dynamic Factor Model are backtested with data of 2018 and 2019. The results suggest rolling Vector Autoregression is the most robust among the three for prediction, and expose the weakness of static VAR during market turbulence.

1 Introduction

Dry cargo market is known to be driven by major bulk including iron ore, coal and grain by practitioner. For example, given that high commodity price is not due to lack of supply, higher commodity prices reflects higher demand of the commodity which in turn translates to more transportation needs to be reflected in Freight rate. Lower commodity prices on the other hand is more complex as it can both reflects lower consumption demand for the commodity but higher physical stock demand especially for non- time deteriorated commodity such as iron ore.

Literature can be found discussing factors for forecasting spot freight rates. In the study conducted by Zhang, Zeng and Zhao (2014), 4 Routes Time Charter Average (4TC) FFA for next quarter and 6-month Time Charter (TC) contracts price are found to be cointegrated with 4TC Baltic Capesize Index (BCI) which is an index for spot price. Details of BCI and relevant routes are in the Appendix.

According to Tsioumas and Papadimitriou(2018), bidirectional lead-lag relationship between BCI and price of iron ore and coal can be found; their finding includes higher commodity prices boost freight rate in the short run while suppressing trading in the long term and similarly, lower commodity prices depress freight rate in the short run while boosting trading in the long term.

While the above research focuses on predicting spot freight rates, Return Index of FFA created by rolling futures contracts is also important to freight trader as they can be traded as a pure financial instrument while the spot freight rate market involves the carry forward cost of not using the vessels. Hence, this study focuses on predicting the log difference of Return Index in the very near future with t+1 forecast with information available up to time t using dynamic model, rolling VAR and static VAR.

2 Data

Two data sets with full period from 2015 to 2019 are under study. One is daily price for FFA monthly contract which can be found on Bloomberg. The other is the daily iron ore Index (IODEX) which can be found on Wind. Details of obtaining the dataset can be found in the Appendix.

Return Index To trade futures systematically, the first step is often to construct continuously investable derivative which is called Return Index here. In this article, on non-rolling date t Return Index would have return rate on month M defined as:

$$r(t) = FFA_{M+2}(t+1)/FFA_{M+2}(t) - 1 \tag{1}$$

On rolling date t defined as the end of the month in this article, return rate is defined as:

$$r(t) = FFA_{M+3}(t+1)/FFA_{M+3}(t) - 1 \tag{2}$$

Once return rate is obtained, price of the Return Index $P(t)$ can be obtained by an initial investment of 100 with cumulative production of $1 + r(t)$:

$$P(t+1) = 100 * \prod_{i=1}^{t}(r(i) + 1) \tag{3}$$

IODEX According to S & P global, IODEX is a benchmark assessment of the spot price of physical iron ore plus the transportation fee to Qingdao (Cost and Freight). The assessment is based on a standard specification of iron ore fines with 62 per cent iron among other elements. The data is shifted forward for 1 day, to ensure the report of the price is available when making the forecast.

3 Methodology

In this study, a training period which is from 2015-01-01 to 2017-12-31 is analysed. Cointegration rank test is applied to validate if there is cointegration between IODEX and Return Index. The bivariate time series is also fitted into a VAR for Granger Causality, and Impulse Response Analysis.

To analyse the predictive ability of IODEX and Return Index's own lags on Return Index, 2018 and 2019 are selected as two independent testing periods.

Firstly, a static VAR model is estimated with data of training period through OLS assuming that the true relationship is static. When there is new data in the testing period, during the 1 step ahead prediction only the endogenous variables are provided coefficients are not changed.

Secondly, a rolling VAR model is estimated with recent 200 days data. When there is new data in the testing period, during the 1 step ahead prediction, the endogenous variables are provided and coefficients re-estimated.

Finally, dynamic factor model is estimated with all the data up to time t each time when walking through the test sets but the model is updated by MLE with Kalman Filter, which allows the pattern to be dynamic without specifying a rolling window.

3.1 Cointegration and VECM

According to Ruppert (2011) and adapted to our setting, A bivariate time series is cointegrated if both component series are I(1) and their r independent linear combinations are I(0) for some r larger than 0 and less than 2.

To test for cointegration, we can first put the bivariate time series into VECM form and test for the rank of Π

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + \Pi Y_{t-1} + \mu + \Phi D_t + \epsilon_t \tag{4}$$

where $Y_t = (Y_{1,t}, Y_{2,t})^\top$ which is the bivariate time series of the study (IODEX and Return Index)and $\Pi = \alpha\beta^\top$, if the rank of π is zero, it would suggest that the error correction term (ΠY_{t-1}) is not useful and hence there is no cointegration, the model can reduce to VAR(p-1) without the error correction term.

3.2 VAR

According to Lütkepohl (2007), VAR(p) model can be written into such form

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad t = 0, \pm 1, \pm 2, \ldots \tag{5}$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a (K×1) random vector, the A_i are fixed (K×K) coefficient matrices. For our bivariate time series, K=2. This is a system with endogenous variable described by its own lags and lags of other variables in the system. y_t is required to be I(0).

3.3 Granger Causality

We can test for the absence of Granger causality (1969) by estimating the following VAR model:

$$Y_t = a_0 + a_1 Y_{t-1} + \ldots.. + a_p Y_{t-p} + b_1 X_{t-1} + \ldots.. + b_p X_{t-p} + u_t \tag{6}$$

$$X_t = c_0 + c_1 X_{t-1} + \ldots.. + c_p X_{t-p} + d_1 Y_{t-1} + \ldots.. + d_p Y_{t-p} + v_t \tag{7}$$

where H_0: b1 = b2 = ... = bp = 0, against HA: 'Not H_0', is a test that X does not Granger-cause Y. Zhang, Zeng and Zhao (2014) conducted a Grander Causality Test to confirm Iron Ore Price Granger-cause BCI following the Toda and Yamamoto (1995) procedure, but in this experiment, Y and X are log difference of Return Index and IODEX (both are stationary according to ADF test) so that ordinary Grander Causality Test can be used.

3.4 Impulse Response Analysis

According to Lütkepohl (2007), The impulse responses and forecast error variance decompositions of a VAR model are obtained from its pure MA representation. IR analysis is used to analyse given a positive or negative shocks happened to the independent variables, what is the reaction of the dependent variables. In this study, it is used to analysed shock on IODEX's effect on Return Index and vice versa.

3.5 Dynamic Factor Model (DF)

Dynamic factor model is an extension of static factor model. Using only 1 lag of the factor, it can be written in the following state space form:

$$\begin{aligned} y_t &= A + B s_t + u_t \\ s_t &= \Phi s_{t-1} + v_t \end{aligned} \tag{8}$$

and

$$\begin{aligned} u_t &\sim N(0, R) \\ v_t &\sim N(0, Q) \end{aligned} \tag{9}$$

where s_t is the state vector **unobservable**, while y_t is the actual measurement in this case it is the price vector of Return Index and IODEX. $E[u_t u_t'] = R$ and $E[v_t v_t'] = Q$ are the covariance matrix for u and v, where u is known as measurement error, v known as innovation. Let N = number of endogenous variables = 2, and K = number of factor = 1, A is N*1 matrix used as intercept, B is N*K coefficient matrix, Φ is K*K coefficient matrix

With variance of estimation of S_t given information up to t-1 i.e. $s_{t|t-1}$ defined as:

$$P_{t|t-1} = E\left[\left(s_t - s_{t|t-1}\right)^2\right] \tag{10}$$

and variance of estimation of S_t given information up to t i.e. $s_{t|t}$ defined as:

$$P_{t|t} = E\left[\left(s_t - s_{t|t}\right)^2\right] \tag{11}$$

Similar setting for estimation of y_t given information up to t:

$$y_{t|t-1} = E_{t-1}[y_t] \tag{12}$$

and its variance

$$V_{t|t-1} = E\left[\left(y_t - y_{t|t-1}\right)^2\right] \tag{13}$$

With the notation above, kalman filter which is used to update our knowledge of the state vector i.e. $s_{t|t}$ and $p_{t|t}$ with the new data points available. Given given $s_{1|0}$ and $p_{1|0}$, Kalman filter can be summarised into 3 steps:

$$\begin{array}{ll}\text{Prediction:} & s_{t|t-1} = \Phi s_{t-1|t-1} \\ & P_{t|t-1} = \Phi P_{t-1|t-1}\Phi' + Q \\ \text{Observation:} & y_{t|t-1} = Bs_{t|t-1} \\ & V_{t|t-1} = BP_{t|t-1}B' + R \\ \text{Updating:} & s_{t|t} = s_{t|t-1} + P_{t|t-1}B'V_{t|t-1}^{-1}\left(y_t - y_{t|t-1}\right) \\ & P_{t|t} = P_{t|t-1} - P_{t|t-1}B'V_{t|t-1}^{-1}BP_{t|t-1}\end{array} \tag{14}$$

Assuming $y_t \sim N\left(y_{t|t-1}, V_{t|t-1}\right)$, with the state vector knowledge described as above, the log-likelihood y_t can be described as:

$$\begin{aligned}\log L_t = & -\frac{N}{2}\log(2\pi) - \frac{1}{2}\log\left|V_{t|t-1}\right| \\ & -\frac{1}{2}\left(y_t - y_{t|t-1}\right)' V_{t|t-1}^{-1}\left(y_t - y_{t|t-1}\right)\end{aligned} \tag{15}$$

By maximising this log-likelihood through numerical methods such as newton method, we obtained the parameters ($\{A, B, \Phi, R, Q\}$) needed for the Dynamic Factor Model in state space form.

4 Empirical results

4.1 Training Period Analysis

According to Johansen test, if using trace mthod, the bivariate time series are cointegrated (Table 1). if using maximum eigenvalue method, the result will be the opposite(Table 2). By fitting a VECM, the cointegration matrix of VECM being identity matrix suggests the error correction term is not useful, only the component time serie own leg is used. Therefore, although cointegration are suggested by trace method, VAR model is used for the back-test study.

Table 1: Johansen cointegration test using trace test 5%

r_0	r_1	test statistic	critical value
0	2	19.74	15.49
1	2	7.259	3.841

Table 2: Johansen cointegration test using maxeig test 5%

r_0	r_1	test	critical value
0	1	12.49	14.26

Table 3: Cointegration relations for loading-coefficients-column 1

	coef	std err	z	P > |z|	[0.025	0.975]
beta.1	1	0	0	0	1	1
beta.2	0	0	0	0	0	0
const	-4.1047	0.054	-76.54	0	-4.21	-4

Table 4: Cointegration relations for loading-coefficients-column 2

	coef	std err	z	P > |z|	[0.025	0.975]
beta.1	0	0	0	0	0	0
beta.2	1	0	0	0	1	1
const	-2.8999	0.166	-17.487	0	-3.225	-2.575

To use the VAR model and related Granger Causality and Impulse Response Analysis, a ADF unit root test is performed on log-differences of IODEX and Return Index. According to AIC, VAR(3) is selected and its residuals have no auto-correlation up to lags 10 according to Portmanteau-test.

From the result of Granger Causality Test (ssr based F test F=6.7098 , p=0.0002, number of lags (no zero) :3), Return Index does Granger Cause Close Price but not vice versa (number of lags (no zero) 3 ssr based F test: F=1.6123 , p=0.1848). Therefore, if the purpose is to forecast Return Index, further study can test the result of a AR model.

Note that the IODEX is shifted forward for one day to ensure availability, so it's only knowledge of Return Index with information up to t helps to 'predict' t-1 IODEX (giving it back its original timestamp). This 'prediction' has little practical meaning. Firstly, this prediction contains look-ahead bias if the report is actually available without lag of 1 day, the price for iron ore at t-1 is definitely known at t so this result is not useful for iron ore trader who has real time information. Secondly, IODEX uses Cost and Freight (CFR), hence it does not equal to actual Iron Ore market price.

From the impulse response analysis (See Figure 2), given a positive shock on return index, IODEX would go up for a very short period. The impact of a positive shock on IODEX to return index is ambiguous given the large confidence interval around zero.

Both IODEX and Return Index's ACF cut off after lag 1, hence Factor Model with factor lag order = 1 is fitted. Assumption of log return of the bivariate time series confirmed by the Q-Q plot albeit suffering from fat tail problem.

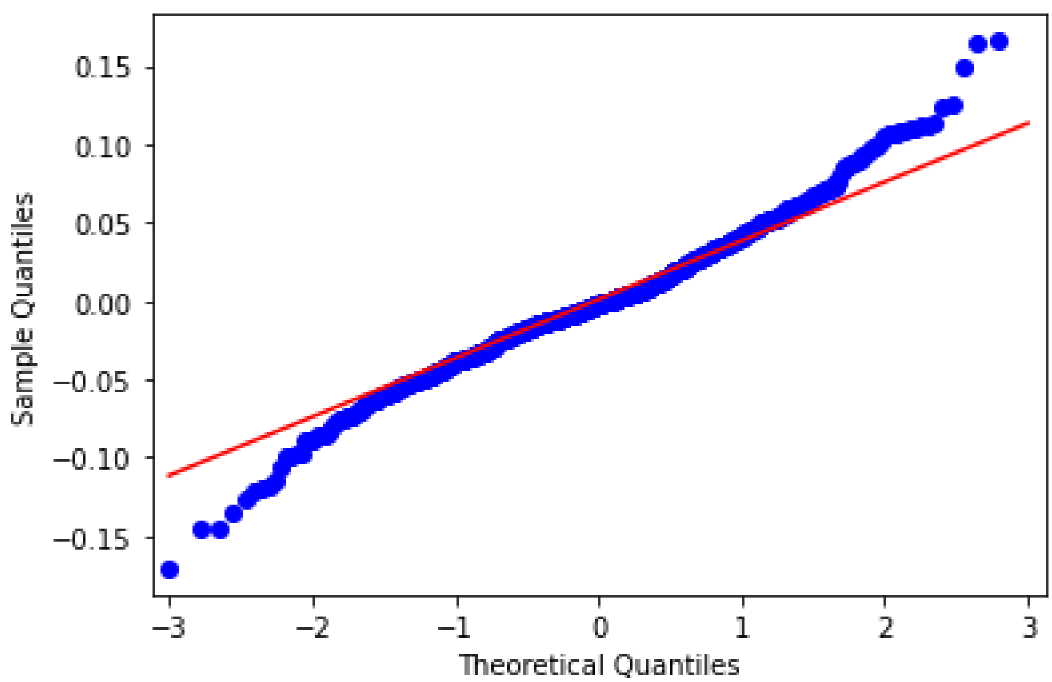

Figure 1: QQ plot for log return of Return Index

Other details of model parameters of VECM, VAR and Dynamic Factor Model (DF) are given in the Appendix.

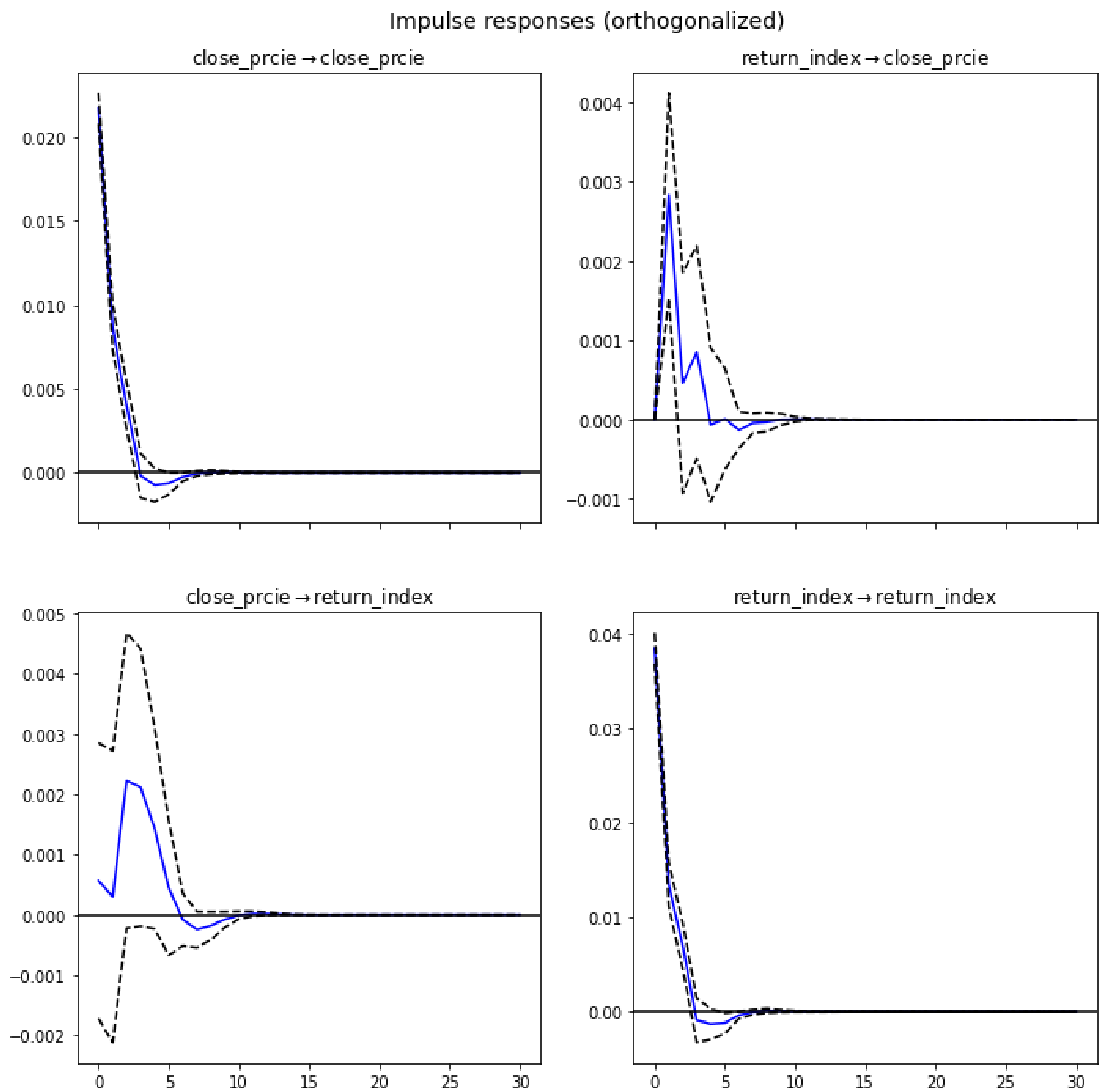

Figure 2: Close price is IODEX.

4.2 Backtesting

Table 5: 2018 back-test

2018	Static VAR	Rolling VAR	DF
RMSE	0.0293	0.0300	0.0316
Accuracy	0.6444	0.6722	0.5944
Sharp Ratio	4.9793	4.7257	3.7171
MDD	-0.96	-0.96	-0.92

In 2018, both rolling and Static VAR have similar RMSE, Directional Accuracy and Sharpe Ratio. This result might be explained by the fact that 2018 is a year with less disruptive events and closer to the training period and hence its characteristics are similar to the training period. In this year, DF's performance is worse than those two.

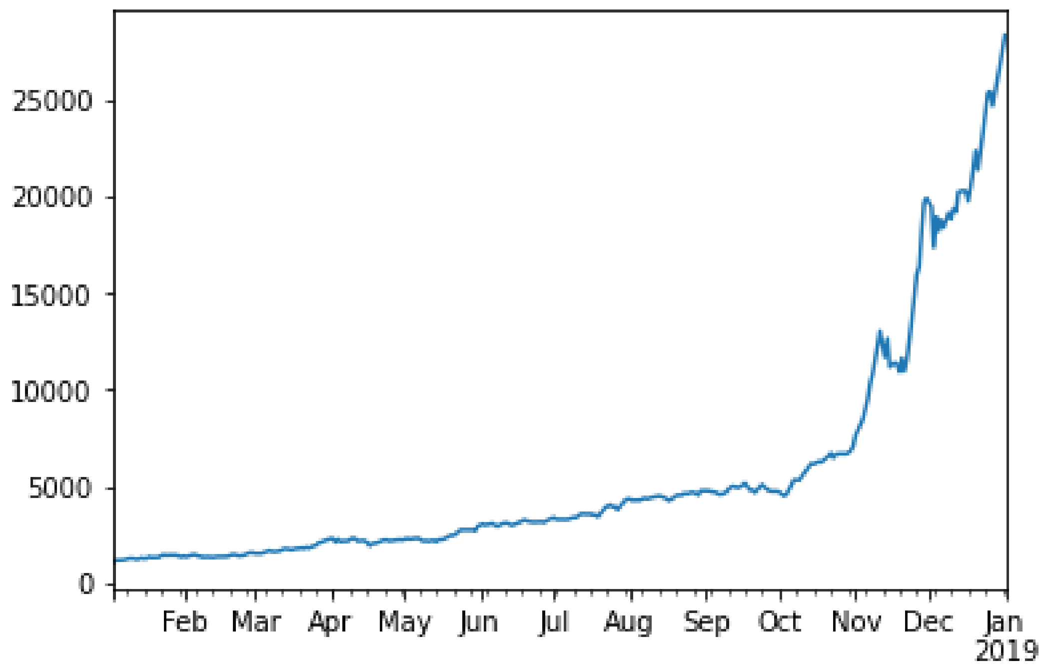

Figure 3: 2018 static VAR strategy back-test value time series

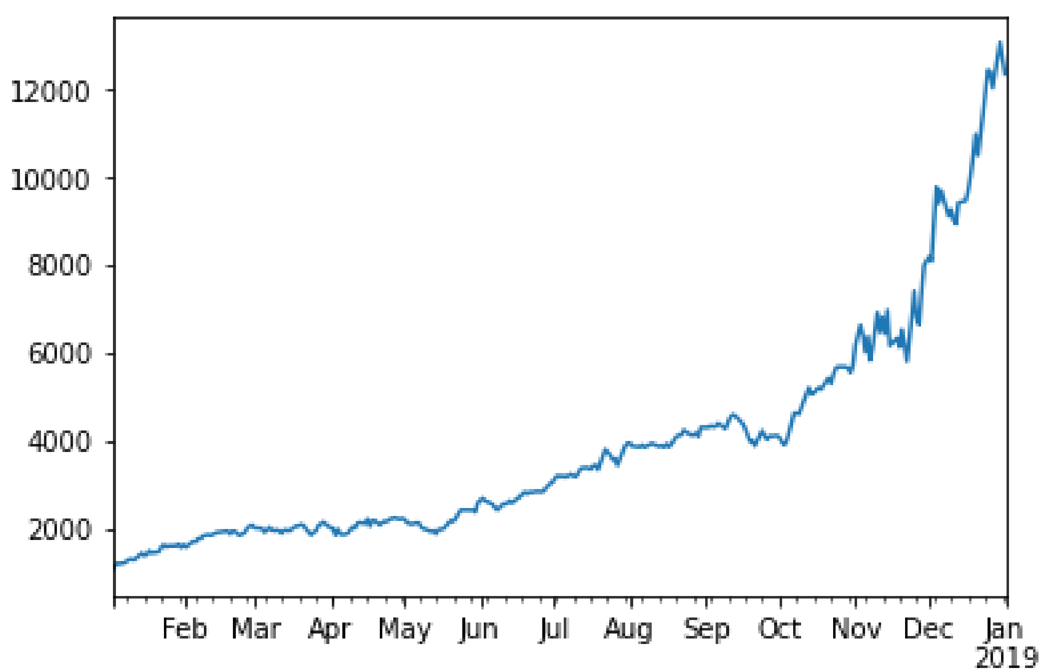

Figure 4: 2018 DF strategy back-test value time series

Table 6: 2019 back-test

2019	Static VAR	Rolling VAR	DF
RMSE	0.0416	0.0409	0.0408
Accuracy	0.6295	0.6267	0.5877
Sharp Ratio	3.7493	4.4683	2.3074

In 2019, all model has larger rmse compare to that of 2018. One reason could be the **2019 Vale Incident** limiting the iron ore supply which breaks up the relationship between IODEX and Return Index for higher IODEX doesn't imply higher demand for transportation. It can be seen that static VAR has significant performance drop compared to rolling VAR and DF most likely due to the model cannot adjust its coefficients even during the period the relationship breaks up.

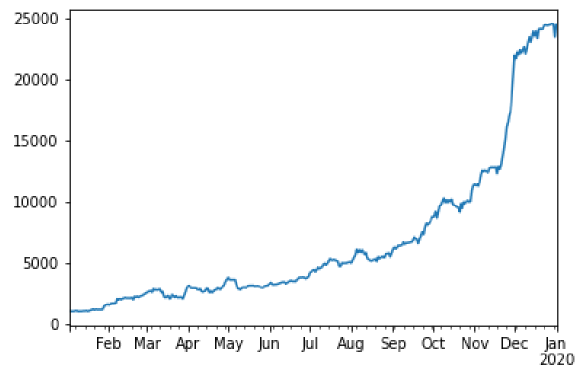

Figure 5: 2019 static var strategy back-test value time series

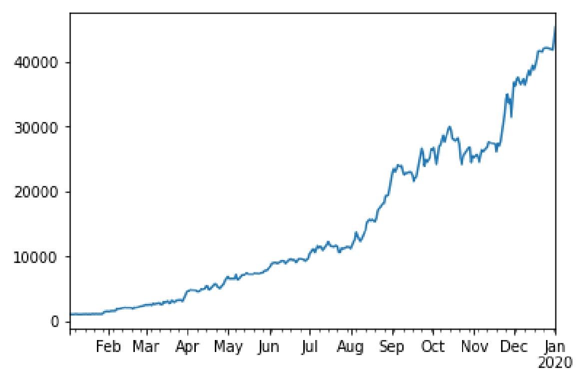

Figure 6: 2019 rolling var strategy back-test value time series

It can be seen that due to the VAR model cannot adjust according to the new pattern. In 2019, it has sub performance compared to rolling VAR all the way unti when the situation becomes normal again during approximately November of 2019 and January of 2020. While DF continues to be the worst performer, its performance drop compared to static VAR model is not as great.

5 Conclusion

Rolling VAR with log return of IODEX and log return of Return Index can provide an effective 1-step-ahead prediction for log return of Return Index (derivative of M+2 C5 FFA) both in normal market condition, and in a year when the market has a disruptive incident, while a static VAR performs worse once a major disruptive event occurs. Univariate Dynamic Factor Model fitted on this Bivariate Timeseries always performs the worst suggests that they are not moved by the same factor and might be affected by fat tails problem. As IODEX doesn't granger cause log return of Return Index during the training period, which is unexpected, further study can try to use static AR, rolling AR and AR in state-space form updated through MLE with Kalman filter to confirm IODEX doesn't have significant contribute to the prediction.

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