Asset Allocation through Recurrent Neutral Network

Model Selection Modification

There are small discrepancies in the predictability of the RNN model with same learning rate and number of epochs. The discrepancies are resulted from the optimization process in network backpropagation through time. Considering these discrepancies, to improve our final model, every time the same model is trained five times and only the model achieves the best prediction result on the validation data is selected as our final model before feeding into the unseen test data. The following sections, all models are selected in this way.

Here, we still use the two different models that we mentioned in the former report to obtain investment portfolio.

Model 1: With recurrent neural net method, we can predict weekly trend of our target index movements and assign weights accordingly.

Model 2: With the daily adjusted price of highly correlated Index, we use feedforward network method to predict the price of our target Index . Then, with Markovitz portfolio theory, we adjust the portfolio weight to get the optimized sharp ratio.

Validation Section

Objective

The main purpose of this section is to investigate the consistency of the performance in our two trading strategies developed through recurrent neural net method and feedforward network method.

The validation section below describes four different validation methods.

1. In the first stage, the model is checked against different kinds of assets.
2. In the second stage, model is checked against the same stock but 5 different periods of equal lengths.
3. Next, the model is validated against periods with different lengths
4. Finally, model is run and tested on synthetic data generated through GARCH model.

Validation Method 1 & results

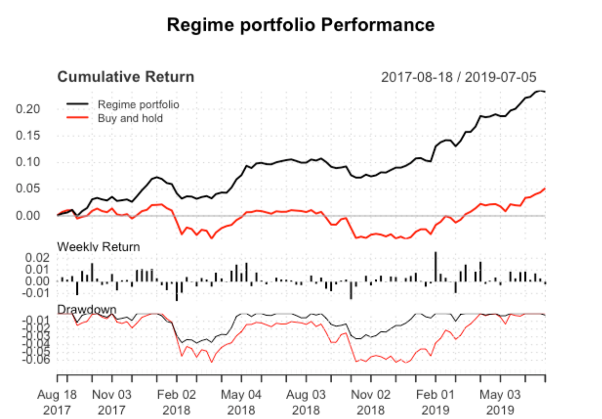
Model 1

The model 1 is run over three different kinds of assets, and the capital is allocated in a fixed investment ratio 0.8/0.2, according to our model predicting up or down. Rebalancing occurs on a weekly basis. We have chosen Oil for commodity, FTSE 100 and Daxi for stock index and HSBC for corporate stock and the results are shown as follows.

We are able to obtain above 60% prediction accuracy, 64.6%, 84.4% ,60.6% and 71.7% for 'FTSE 100', 'Oil' ,Daxi and 'HSBC' respectively.

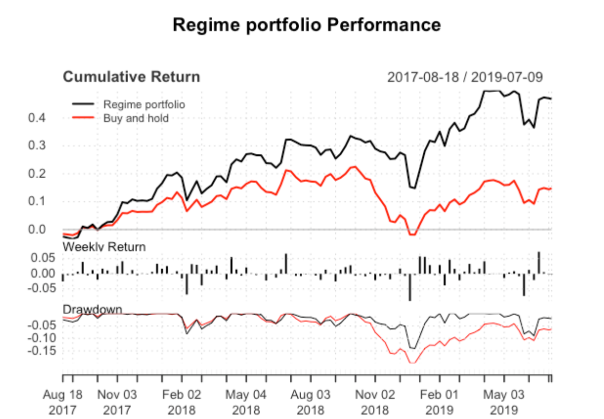
From figure 1, we can see that above-average prediction accuracy has translated into promising financial returns. We observe that our regime portfolio outperforms the simple buy and hold portfolio in all three asset classes by at least 10% in term of overall cumulative returns. Consistently high sharpe ratios indicates that the risks are managed well and we have avoided from suffering huge drawdowns, like in late 2018.

FTSE 100 0.6464646



	Regime portfolio	Buy and hold
Cumulative Return	0.23293421	0.05187061
Annualized Standard Deviation	0.04813690	0.05683221
Annualized Return	0.11626270	0.02691800
VaR	-0.12818339	-0.21945694
Worst Drawdown	0.03784954	0.06361315
Annualized Sharpe Ratio (Rf=0%)	2.41525122	0.47363977

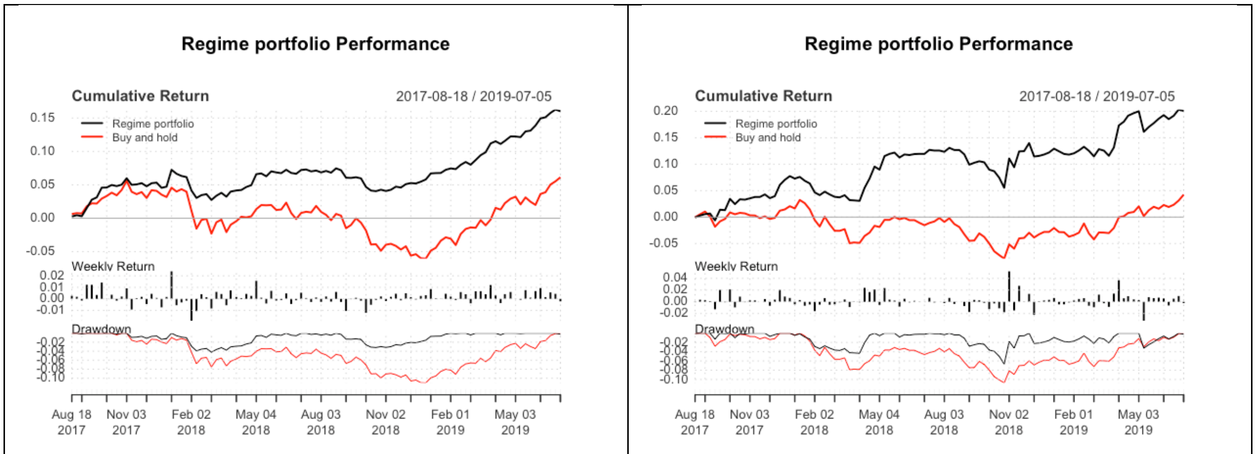
Oil 0.8484848



	Regime portfolio	Buy and hold
Cumulative Return	0.4682027	0.14768051
Annualized Standard Deviation	0.1841588	0.13573098
Annualized Return	0.2210367	0.07425386
VaR	-0.6202423	-0.48739541
Worst Drawdown	0.1403778	0.19870093
Annualized Sharpe Ratio (Rf=0%)	1.2002510	0.54706640

Daxi 0.6060606

Hsbc 0.7171717



	Regime portfolio	Buy and hold
Cumulative Return	0.16019097	0.06131286
Annualized Standard Deviation	0.04304512	0.06978655
Annualized Return	0.08117071	0.03174964
VaR	-0.12245513	-0.26893959
Worst Drawdown	0.04203901	0.11036182
Annualized Sharpe Ratio (Rf=0%)	1.88571208	0.45495356

	Regime portfolio	Buy and hold
Cumulative Return	0.20075845	0.04246418
Annualized Standard Deviation	0.08358605	0.07277024
Annualized Return	0.10086555	0.02208416
VaR	-0.20384425	-0.25556941
Worst Drawdown	0.06676335	0.10738137
Annualized Sharpe Ratio (Rf=0%)	1.20672703	0.30347794

Figure 1: model 1 performance on different kinds of asset

Model 2

We applied the same procedure with model 2 where predicted weekly returns are fed to generate Markowitz investment portfolio with adjustable weights each week. The results are as follows. From figure 2, we can observe that the predicted stock prices/returns follow closely with the actual price/returns data in all asset classes.

In addition, the Mean Square Error from table 1 for HSBC is higher than that of stock index may suggest that corporate index is more volatile and harder to predict than stock index.

Comparation of Standardized Test MSE：

FTSE	0.013353618
DAXI	0.0070694825
HSBC	0.09240311

Table 1: model 2 prediction accuracy on different kinds of asset

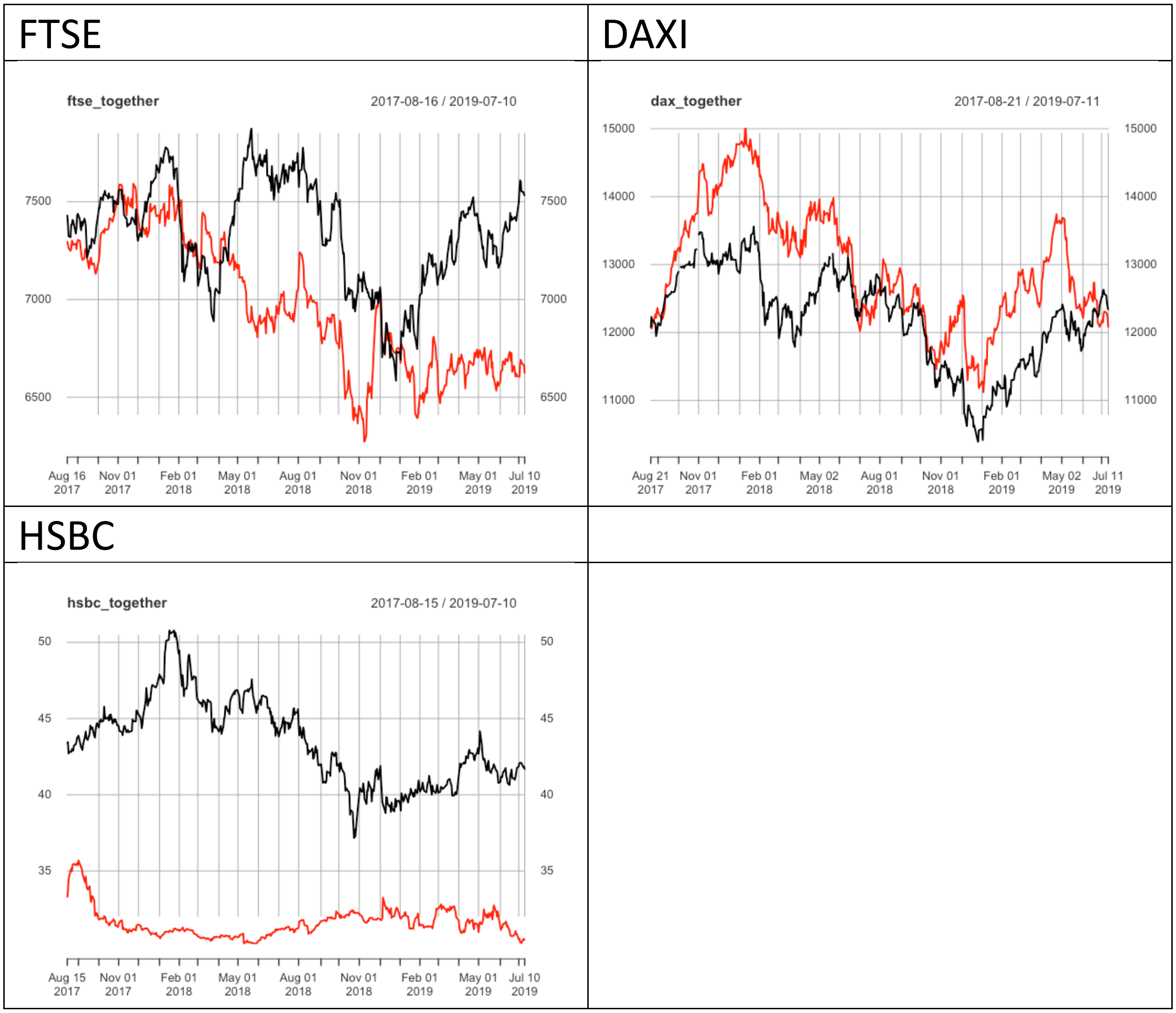
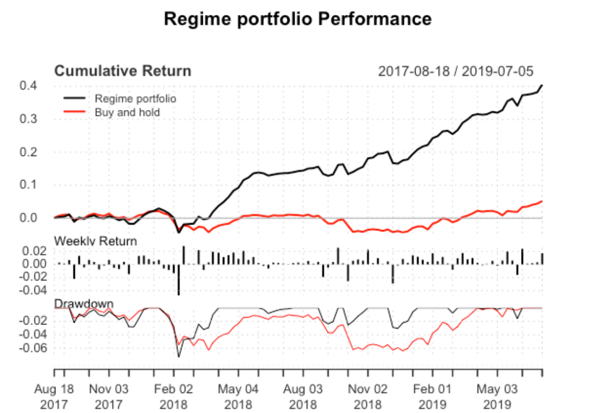


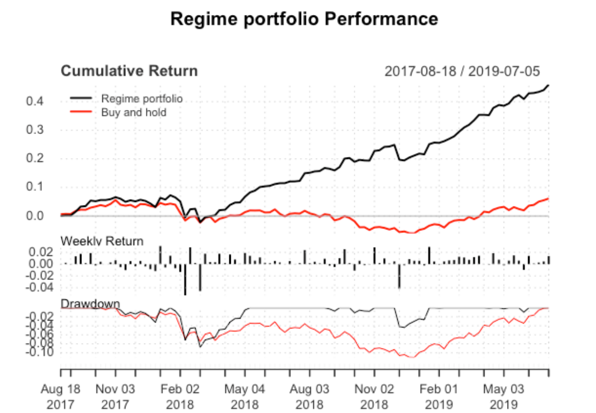
Figure 2: model 2 prediction on different kinds of asset

FTSE



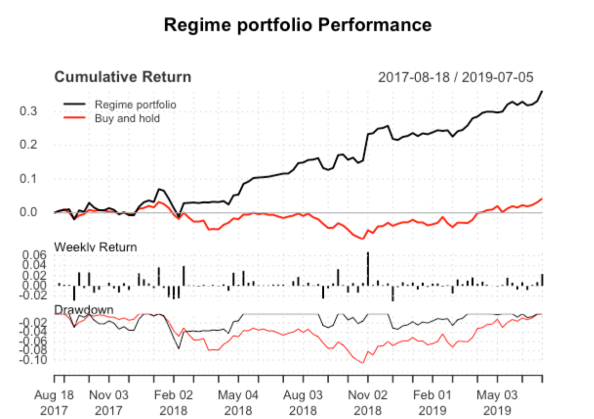
	Regime portfolio	Buy and hold
Cumulative Return	0.40606325	0.05187061
Annualized Standard Deviation	0.08315240	0.05683221
Annualized Return	0.19602408	0.02691800
VaR	-0.28352120	-0.21945694
Worst Drawdown	0.07352906	0.06361315
Annualized Sharpe Ratio (Rf=0%)	2.35740734	0.47363977

DAXI



	Regime portfolio	Buy and hold
Cumulative Return	0.46023113	0.06131286
Annualized Standard Deviation	0.09224259	0.06978655
Annualized Return	0.22000852	0.03174964
VaR	-0.32471787	-0.26893959
Worst Drawdown	0.08768891	0.11036182
Annualized Sharpe Ratio (Rf=0%)	2.38510764	0.45495356

HSBC



	Regime portfolio	Buy and hold
Cumulative Return	0.36304157	0.04246418
Annualized Standard Deviation	0.10326474	0.07277024
Annualized Return	0.17666069	0.02208416
VaR	-0.23659563	-0.25556941
Worst Drawdown	0.07566016	0.10738137
Annualized Sharpe Ratio (Rf=0%)	1.71075520	0.30347794

Figure 3: model 2 performance on different kinds of asset

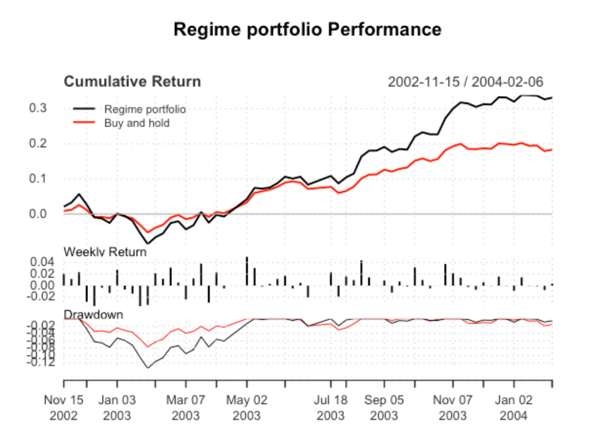
Validation Method 2 & results （choose fix and floating data）

In this validation method, instead of comparing how our model performs on different classes of assets, we are applying our model with only one stock, HSBC for model 1 and DAXI for model 2 but for different periods in time. In particular, 20-year period of HSBC stock prices is equally divided into four subsets, each subset contains 5-year data. Within each subset, the model is run after the train, validate and test split and only the test results are shown here

Model 1 for HSBC

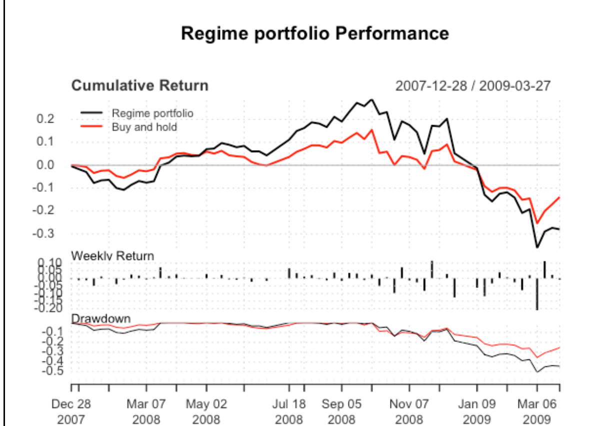
As seen from figure 4, prediction rates on test data are consistently above 65%. This suggests that our model might not necessarily be time dependent as no significant fluctunation observed across the four different test periods. In terms of our portfolio results, financial crisis period(2007 – 2009) is the only period we have seen an underperforman against the 'Buy and Hold' approach. In particularly, the worst drawdown during the 07-09 generated from our model is worse than that of the 'Buy and Hold' approach.This suggests that our model prediction accuracy will be influenced on crisis period.

First 5 yesrs. 0.7575758



	Regime portfolio	Buy and hold
Cumulative Return	0.3316079	0.18354432
Annualized Standard Deviation	0.1388093	0.08308953
Annualized Return	0.2765145	0.15448105
VaR	-0.4260987	-0.25984244
Worst Drawdown	0.1348877	0.07627698
Annualized Sharpe Ratio (Rf=0%)	1.9920458	1.85921191

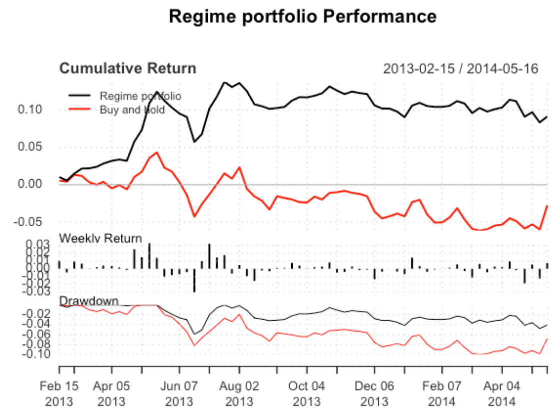
Second 5 yesrs. 0.6865672



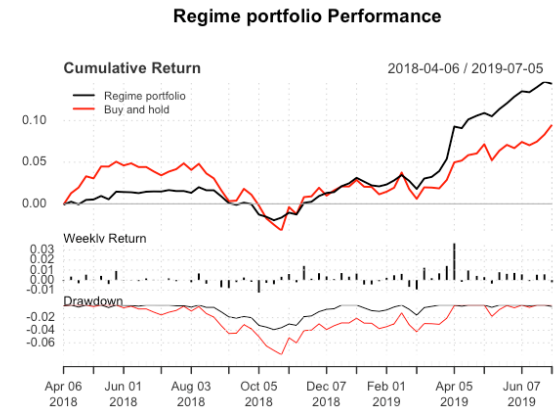
	Regime portfolio	Buy and hold
Cumulative Return	-0.2800177	-0.1389334
Annualized Standard Deviation	0.3749865	0.2469162
Annualized Return	-0.2408381	-0.1179064
VaR	-1.5813826	-1.0174046
Worst Drawdown	0.5053704	0.3539632
Annualized Sharpe Ratio (Rf=0%)	-0.6422581	-0.4775157

Third 5 yesrs. 0.7313433

Fourth 5 yesrs. 0.6567164



	Regime portfolio	Buy and hold
Cumulative Return	0.09153251	-0.02777520
Annualized Standard Deviation	0.07595764	0.08624061
Annualized Return	0.07144107	-0.02194869
VaR	-0.22510900	-0.31293904
Worst Drawdown	0.05986029	0.10058355
Annualized Sharpe Ratio (Rf=0%)	0.94053829	-0.25450523



	Regime portfolio	Buy and hold
Cumulative Return	0.14429587	0.09489126
Annualized Standard Deviation	0.04954679	0.07113708
Annualized Return	0.11204179	0.07403780
VaR	-0.06162414	-0.22456854
Worst Drawdown	0.03897761	0.07883772
Annualized Sharpe Ratio (Rf=0%)	2.26133291	1.04077647

Figure 4: model 1 performance on HSBC with fix and floating data

Model 2 for DAXI

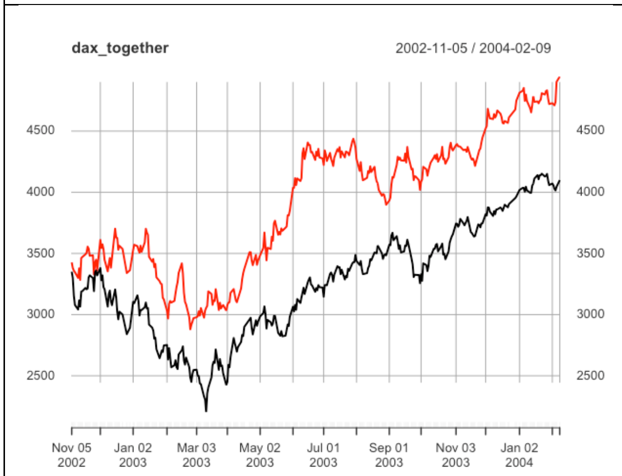
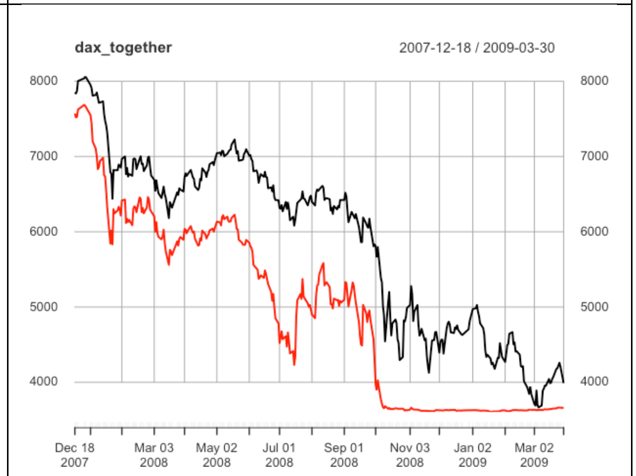
Instead of predicting next week's stock direction, model 2 forecast next week' return of DAX. From the table 2 below, the fact the period between 2004 and 2009 has higher test MSE than any other time periods infers that this period is probably harder to predict due to market volatility, since there had been financial crisis starting 2008 where market suffered uncommon drawdowns. Besides, the portfolio seeting requirement (we can not short sell stock) can be another reason for such bad performance.

Comparation of Standardized Test MSE

1999-01-04 to 2004-02-09	0.015862735
2004-02-09 to 2009-03-30	0.05241912
2009-03-30 to 2014-05-19	0.021704337
2014-05-19 to 2019-07-10	0.011670671

Table 2: model 2 prediction accuracy on DAX with fix and floating data

The chart below shows actual prices change in (black) and our predicted price change in (red)

First 5 yesrs	Second 5 yesrs
	

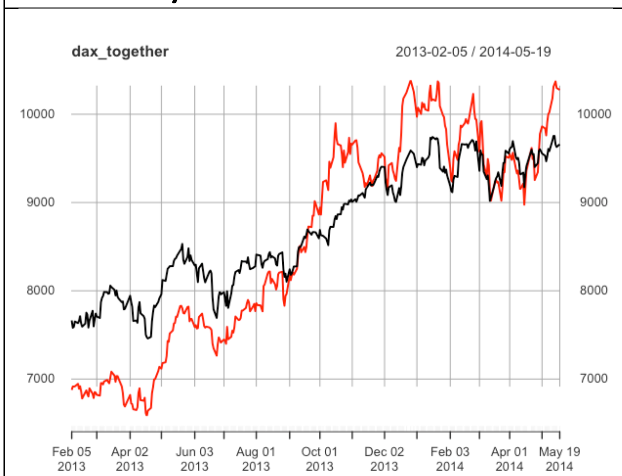
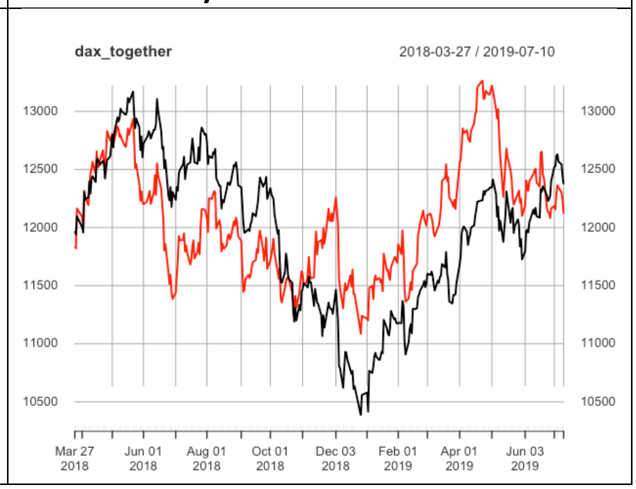
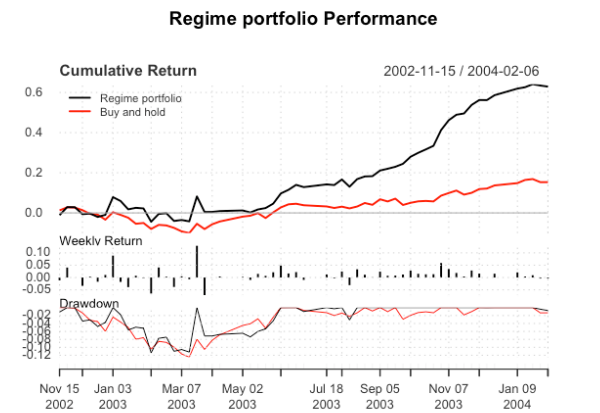
Third 5 yesrs	Fourth 5 yesrs
	

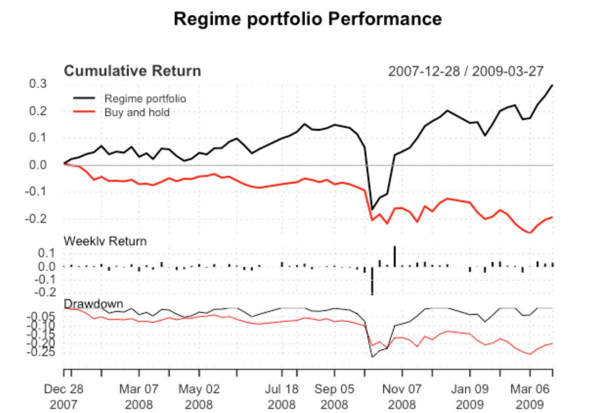
Figure 5: model 2 prediction on DAX with fix and floating data

First 5 yesrs



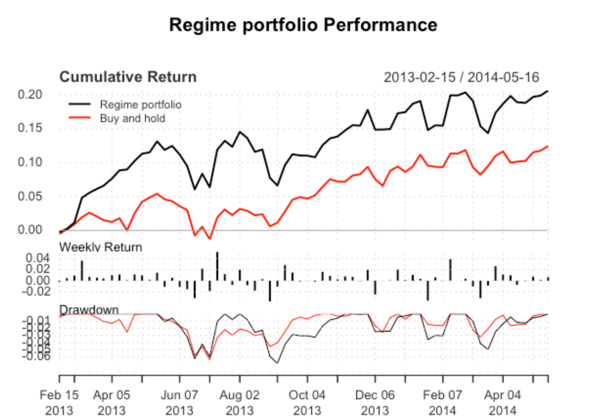
	Regime portfolio	Buy and hold
Cumulative Return	0.6291568	0.1532539
Annualized Standard Deviation	0.2205035	0.1289973
Annualized Return	0.5374987	0.1339082
VaR	-0.5017887	-0.4137587
Worst Drawdown	0.1136570	0.1249416
Annualized Sharpe Ratio (Rf=0%)	2.4375971	1.0380705

Second 5 yesrs



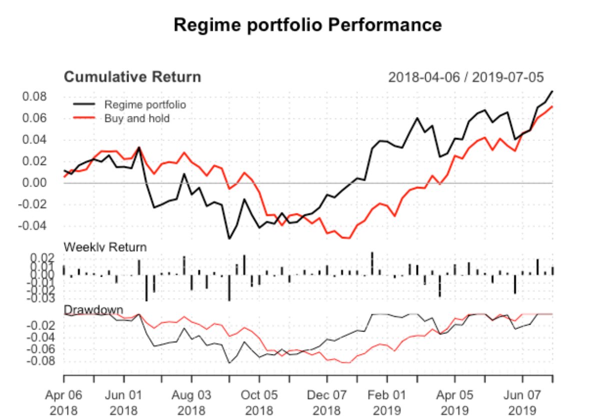
	Regime portfolio	Buy and hold
Cumulative Return	0.3002881	-0.1918911
Annualized Standard Deviation	0.2991467	0.1999660
Annualized Return	0.2463675	-0.1636384
VaR	-1.0841548	-0.7998969
Worst Drawdown	0.2749104	0.2576002
Annualized Sharpe Ratio (Rf=0%)	0.8235673	-0.8183309

Third 5 yesrs



	Regime portfolio	Buy and hold
Cumulative Return	0.20652197	0.12453496
Annualized Standard Deviation	0.11735336	0.08628951
Annualized Return	0.15941758	0.09688353
VaR	-0.37028829	-0.29780913
Worst Drawdown	0.06922338	0.06378979
Annualized Sharpe Ratio (Rf=0%)	1.35844063	1.12277299

Fourth 5 yesrs



	Regime portfolio	Buy and hold
Cumulative Return	0.08632197	0.07179514
Annualized Standard Deviation	0.09105392	0.06294551
Annualized Return	0.06740932	0.05614716
VaR	-0.33881808	-0.22393587
Worst Drawdown	0.08275686	0.08189708
Annualized Sharpe Ratio (Rf=0%)	0.74032304	0.89199624

Figure 6: model 2 performance on DAX with fix and floating data

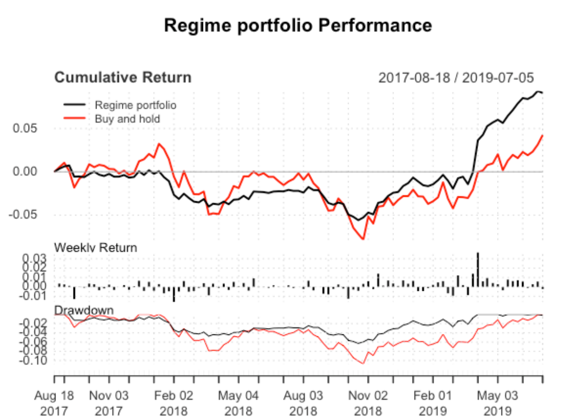
Validation Method 3 & results （short- long term comparation）

After looking at different periods with the same length, we decided to investigate how our model performance on periods with different lengths. 20-year HSBC price data starting from 1999 is split into 5-year(2014-2019), 10-year(2009-2019), 15-year(2004-2019) and 20-year(1999-2019) data sets. Within each of the four data sets, data from 2017 to 2019 is used as test data while the remaining data set is used for model training. We run the same procedure as the above sections for model 1 and model 2.

Model 1

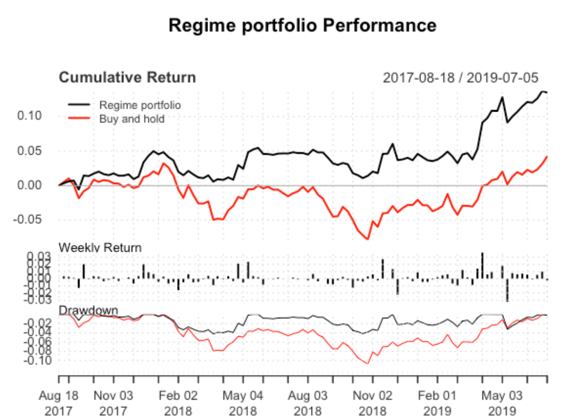
The results are shown below.

Data from 2014 to 2019 0.5555556



	Regime portfolio	Buy and hold
Cumulative Return	0.09101820	0.04246418
Annualized Standard Deviation	0.04731670	0.07277024
Annualized Return	0.04681841	0.02208416
VaR	-0.09276265	-0.25556941
Worst Drawdown	0.06271714	0.10738137
Annualized Sharpe Ratio (Rf=0%)	0.98946891	0.30347794

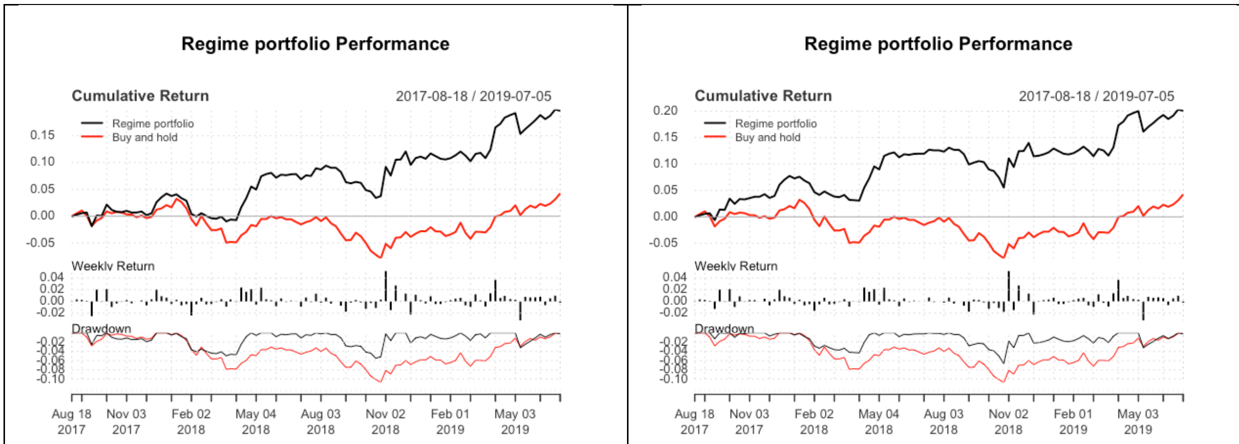
Data from 2009 to 2019 0.6363636



	Regime portfolio	Buy and hold
Cumulative Return	0.13469343	0.04246418
Annualized Standard Deviation	0.06745933	0.07277024
Annualized Return	0.06862441	0.02208416
VaR	-0.19245412	-0.25556941
Worst Drawdown	0.04208078	0.10738137
Annualized Sharpe Ratio (Rf=0%)	1.01727090	0.30347794

Data from 2004 to 2019 0.6767677

Data from 1999 to 2019 0.7070707



	Regime portfolio	Buy and hold
Cumulative Return	0.19619274	0.04246418
Annualized Standard Deviation	0.08634662	0.07277024
Annualized Return	0.09866492	0.02208416
VaR	-0.22568089	-0.25556941
Worst Drawdown	0.05488731	0.10738137
Annualized Sharpe Ratio (Rf=0%)	1.14266099	0.30347794

	Regime portfolio	Buy and hold
Cumulative Return	0.20075845	0.04246418
Annualized Standard Deviation	0.08358605	0.07277024
Annualized Return	0.10086555	0.02208416
VaR	-0.20384425	-0.25556941
Worst Drawdown	0.06676335	0.10738137
Annualized Sharpe Ratio (Rf=0%)	1.20672703	0.30347794

Figure 7: model 1 performance on HSBC with short-long term data

As can be seen from figure 7, model 1's prediction accuracy for the weekly stock direction improves with the size of the training data. With the 20-year data set, the model achieves the highest prediction accuracy of 70%

A similar results pattern in portfolio performance can be observed for all four data sets. With training set size increases, our sharpe ratio also increases marginally. This reflects that training on more historical data could potentially generate slightly better performance.

Model 2 for DAXI

We have observed from the following results that there is significant improvement over test MSE generated from 5-year traning periods to 10-year training period. Besides, from figure9, we can see the plot of 10 ,15 ,20 years do not vary a lot, and the value of cumulative return and annualized sharp ratio remain stable. This might suggest that 10-year dataset might provide an optimal number of training data for our model, which can reduce the calculation times to train our model and yield a reliable prediction result.

Standardized Test MSE results

5- year	0.016561875
10- year	0.00245179
15- year	0.0030338007
20- year	0.0070694825

Table 3: model 2 prediction accuracy on DAX with short-long term data

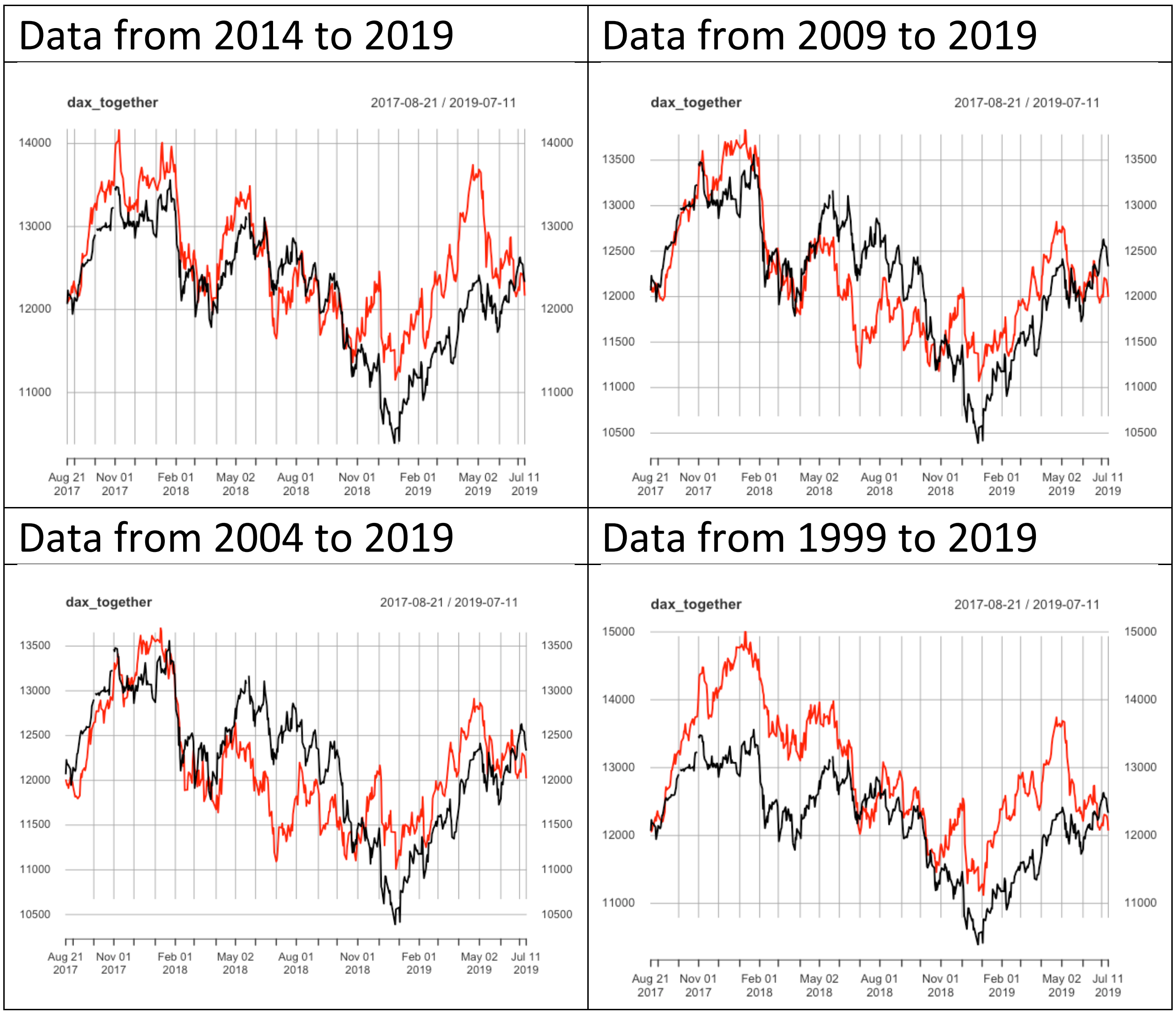
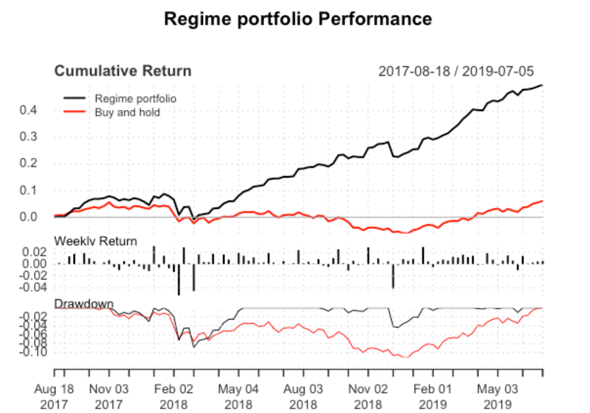


Figure 8: model 2 perdiction on DAX with short-long term data

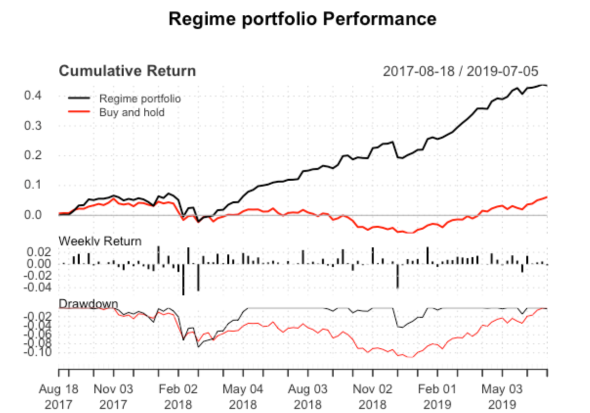
Data from 2014 to 2019	Data from 2009 to 2019

Data from 2014 to 2019



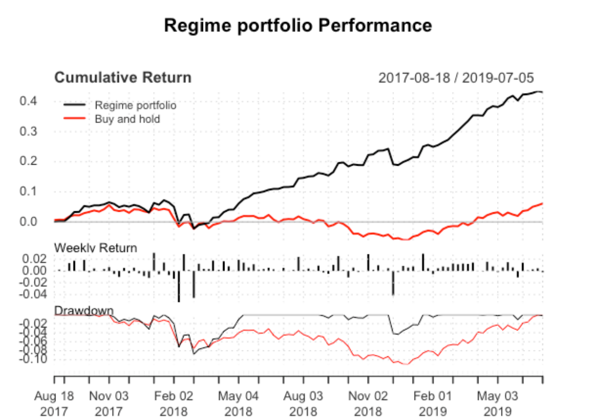
	Regime portfolio	Buy and hold
Cumulative Return	0.49865313	0.06131286
Annualized Standard Deviation	0.09317745	0.06978655
Annualized Return	0.23676578	0.03174964
VaR	-0.32533739	-0.26893959
Worst Drawdown	0.08803427	0.11036182
Annualized Sharpe Ratio (Rf=0%)	2.54102009	0.45495356

Data from 2009 to 2019



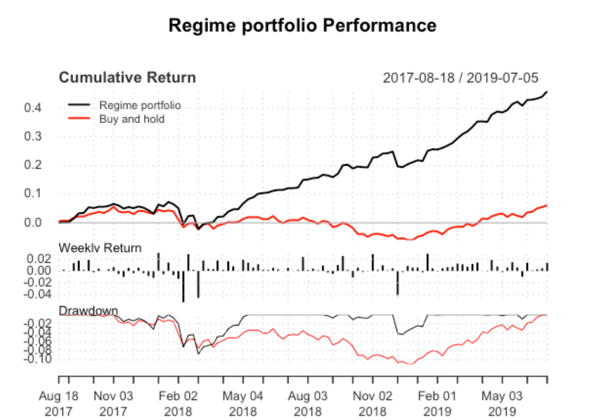
	Regime portfolio	Buy and hold
Cumulative Return	0.43611043	0.06131286
Annualized Standard Deviation	0.09238993	0.06978655
Annualized Return	0.20938147	0.03174964
VaR	-0.32774619	-0.26893959
Worst Drawdown	0.08773065	0.11036182
Annualized Sharpe Ratio (Rf=0%)	2.26628012	0.45495356

Data from 2004 to 2019



	Regime portfolio	Buy and hold
Cumulative Return	0.43194980	0.06131286
Annualized Standard Deviation	0.09195541	0.06978655
Annualized Return	0.20753984	0.03174964
VaR	-0.32639011	-0.26893959
Worst Drawdown	0.08789461	0.11036182
Annualized Sharpe Ratio (Rf=0%)	2.25696172	0.45495356

Data from 1999 to 2019



	Regime portfolio	Buy and hold
Cumulative Return	0.46023113	0.06131286
Annualized Standard Deviation	0.09224259	0.06978655
Annualized Return	0.22000852	0.03174964
VaR	-0.32471787	-0.26893959
Worst Drawdown	0.08768891	0.11036182
Annualized Sharpe Ratio (Rf=0%)	2.38510764	0.45495356

Figure 9: model 2 performance on DAX with short-long term data

Validation Method 4 & result for Model 1 Only （Sanity Check with synthetic data via GARCH model）

A simple way to check if the result of the model is possibly true is to see how the model performs on a set of stock price data simulated through a GARCH model. Each day's open and close prices are simulated through GARCH model with mean 100. To simulate high and low prices, another two independent sets of data are generated through GARCH model with mean 10, then high prices are equal to the sum of open prices and one set of data and low prices are the subtraction of open prices and another set of data.

The objective of the simulation is to produce a good representation of truly random and independent price data from day to day. We have checked that 51% of the times the data shows an 'up' meaning, roughly half of the times the 'price' is greater than the previous day.

The intention is that if our model which is trained and tested on this synthetic random 'price data' can produce a much lower or higher prediction rate than 50% then our model cannot be possible valid.

Without loss of generality, the time unit of the synthetic data is changed from daily to weekly and the length of the GARCH simulated data is chosen to be same as our original S&P 500 training and test set. Hence, the synthetic data is better aligned with the purpose of the sanity check.

The synthetic data is then feed into model for training and testing. The prediction rate is turned out to be 51 %, close to 50% meaning the model is possibly valid.

In terms of generation of GRACH model, we have tried out two different simulation methods.

The difference between method 1 and method 2 is how we set the daily high price and low price of our simulated price data with GARCH. Since some of our influential trading indicators, such as stoh and cci involves using daily high and low price for the calculation, the way we simulate these price data might effect our model prediction.

We generate a group of random numbers from Garch model with mean being 10. Then we assign numbers higher than 10 as the 'high value', and denote the daily high price as the sum of high value and open price data generated with GARCH. Similarly, we assign numbers lower than 10 as the 'low value' and denote the low price as the substraction of open value and low value.

For both method 1 and 2, the occruance of positive and negative daily returns are truly random. However, in method 2 the magnitudes of the differences in the high and open price are greater than that of low and open price. This suggests a potential pattern , which can be seen from figure 11, in our synthetic data produced by method 2. Hence, when we fit our model with data generated by method 2, we can get a prediction accuracy significantly greater than 50% (around 60%). This is further shows than the model can capture patterns within the data while if the data is ramdomly generated including its magnitude (data from method 1) then our model prediction is around 50%, i.e cannot make any meaning prediction. This evidence supports that our model might be valid.

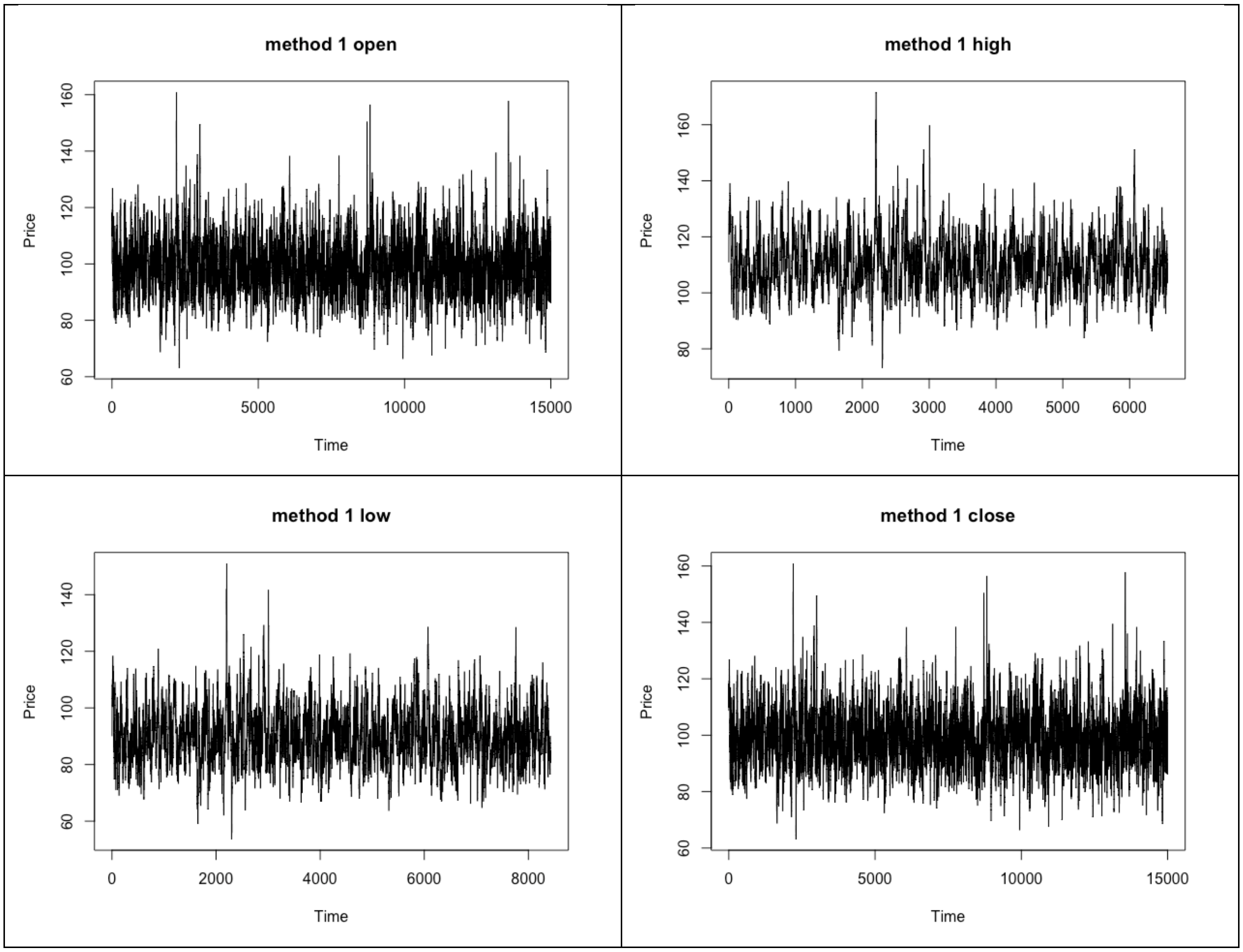


Figure 10: open, high, low, close price of method 1

Model 2

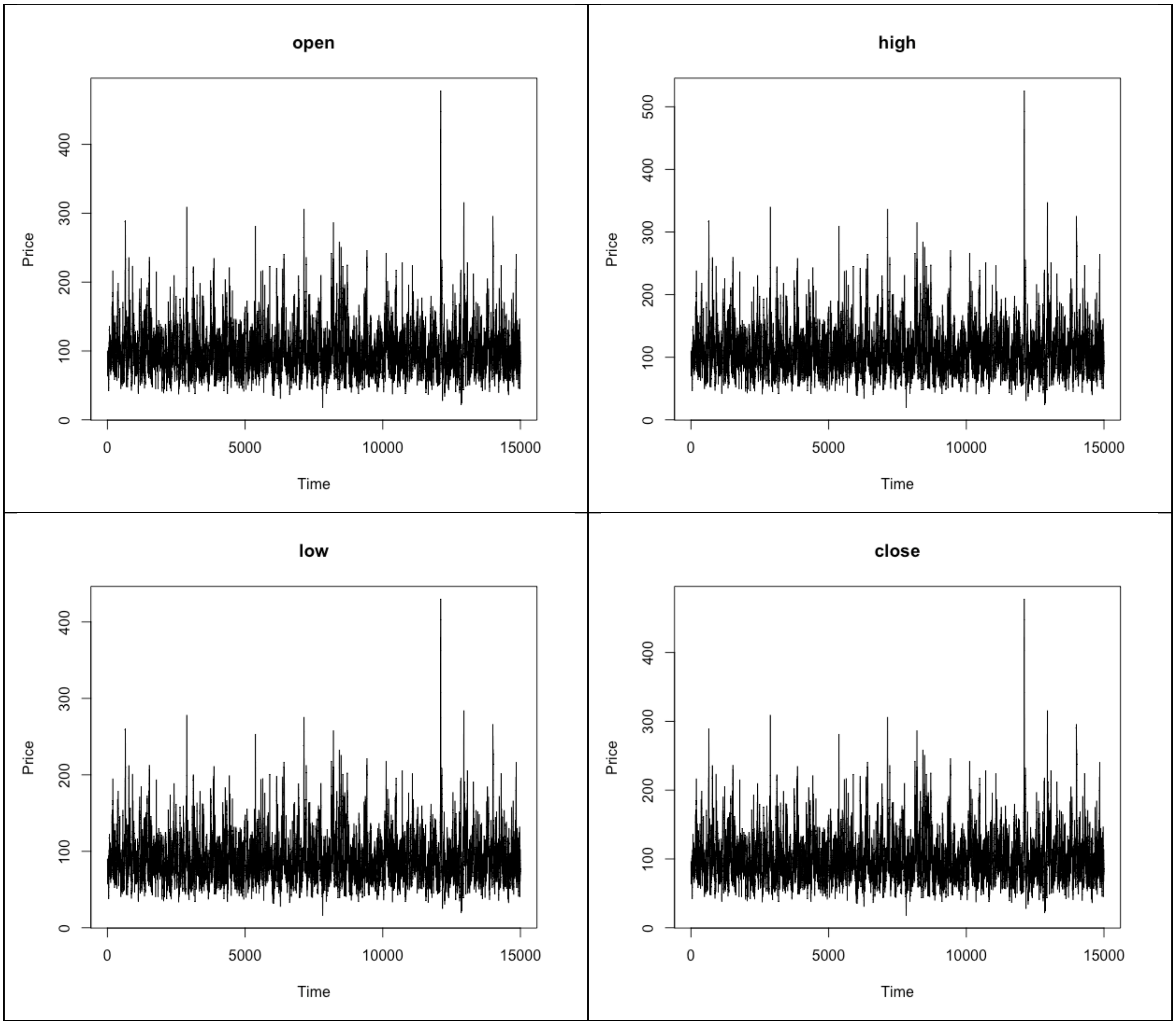


Figure 11: open, high, low, close price of method 2