

# DATA 621 Final – Predicting the Kyat

Sam Reeves

## Exposition

```
library(zoo)
library(tidyverse)
library(MASS)
library(forecast)
library(ggplot2)

rates <- read.csv(
  "https://raw.githubusercontent.com/SamReeves/exchange-rate-prediction/master/rates.csv") %>%
  na.locf()

colnames(rates)[colnames(rates) == "X"] <- "date"
rates <- mutate(rates, date=as.Date(date[[1]]))
str(rates)

set.seed(1337)
```

## Question

Is it reasonable to predict the USD/MMK exchange rate using the historical data for all \*\*\*/MMK exchange rates?

## Cases

Each normal day, the Central Bank of Myanmar used to declare an exchange rate for each of 38 currencies which can be used to buy Kyats. We have nearly 10 years of data, each day is an observation, and there are 38 variables in each observation which are all numerical exchange rates.

## Data collection

This data was scraped from the Central Bank of Myanmar's main website. Since the junta took over, the website has gone offline and this data is no longer available. There was no formal API, however, by building URL strings it was possible to select data from specific time periods.

## Literature Discussion

The following are some sources which heavily influenced this study. The excerpts about them are illustrative concepts which form the foundation for my interpretation of our practical results.

## Monetary Policy and Currency Valuation

BMI.pdf

Indices du jour, such as the Big Mac Index – the local price of a McDonald’s Big Mac – are useless here. There is no McDonald’s in Myanmar, and the lifestyle there has been so secluded for so long, there is probably no basket of goods you could realistically use to establish purchasing power across all use cases of cash.

asian-pac-economic

Over the six-year period 2006-2011, the real exchange rate of the Myanmar kyat appreciated 200 per cent, resulting in the value of the US dollar in Myanmar falling to one-third of its pre-2006 level. While the resource boom is suspected to be the source of the real exchange rate appreciation, administrative controls on foreign exchange and imports had much more impact. Foreign exchange controls limited the convertibility of the kyat to foreign currencies and spurred negotiated transactions of foreign exchange outside the banking sector, hampering the foreign exchange market interventions of the government and Central Bank.

sea\_usd.pdf

“From 2010 to 2017, the currency exchange rates against the USD in SEA countries tended to depreciate. Foreign exchange reserves negatively affect foreign debt, and imports positively affect countries’ exchange rates in the SEA region against the dollar.”

currency\_valuation\_simulation.pdf

These researchers set up a trading game to simulate currency valuation among 116 grad students who were each given a fixed amount of mock foreign currency at the beginning of the game. They found that short term patterns were nearly non-existent and that normal monetary policy basically dictated the valuations, as had been observed in the real world.

J of intl dev

This paper examines the interests of developing nations to “steer clear of exchange rate regimes that lie anywhere between the two extremes or ‘corner solutions’ of credibly fixed or flexible arrangements. They attempt to ask the question of whether or not nations in SEA (though Myanmar is not included – it was very difficult to get credible information at this time) committed a blunder by pegging to USD. They decided that currency boards were inadequate and that the USD peg was sub-optimal, preferring a balanced basket approach.

World Economy 2002 Rajan

In this paper also from 2002, Rajan also decides that currency baskets are the most appropriate of the 9 currency regimes he identifies.

Honey I shrunk

According to Nitsch, one of the puzzles in empirical international trade is the difficulty of finding a large and statistically significant negative effect of exchange rate variability on trade. Surely this huge source of uncertainty and currency risk is one of the greatest barriers to world economic integration. He responds to Rose’s idea that regional currency unions or dollarization can have “an explosive” effect on bilateral or small-group multilateral trade. He shows that accounting for missing data, correcting errors in the initial data, and disaggregating the data by currency union reduces this effect to noise.

Honey the currency union effect hasn’t blown up

Rose writes back, acknowledging his needed corrections. He also recognizes a few other points by Nitsch which are relevant here. He says there are very few observations for country-pairs in real currency unions, trade and control data are missing or incompatible, and any extrapolations onto other countries are flatly ridiculous. Rose will still not abandon his position, ending with, “The mystery continues.” Frankly, suspicious.

## Corruption

junta-skimming.pdf

The United Nations has admitted \$10 million of aid intended for Burmese cyclone survivors has been skimmed off by banks run by the country's military. More recently, much much larger sums have been lost in this way by the UN, including as much as \$150 million in aid given to the previous democratic regime just before the junta declared a state of military law.

emma\_larkin

During Hurricane Nargis, all aid was refused. Even a French plane loaded with supplies was not allowed to even refuel before being forced back into the sky. For decades, under the rule of Ne Win and Tan Shwe, education and healthcare were illegal, and ethnic non-Burmese could have their assets seeds at any time. Conditions have nearly returned to this state.

## Forecasting

bayesian-akaike.pdf

This author expounds on the use of dynamic dependency models that can enhance traditional methods of timeseries methods by allowing a 'decoupling/recoupling' process among different preceeding values across different prediction or association horizons. Seems really cool and effective. We employ some of these ideas to a very elementary degree.

## Model Generation

First, we rebuild the data set with padding so that the y versus x values represent the desired prediction horizon for each. Then, we do a train/test split, and preserve the row numbers of the random samples. The split is 70:30. For each horizon – 7, 14, and 60 days, respectively – we will train a new model on all variables using stepwise selection. We can take a look at the model summaries and residual or QQ plots, and we can make predictions using each of the tests sets we marked.

```
forecast.horizon <- function(days = 1, input = rates) {
  x <- input[1:(nrow(input)-days), 2:39]
  return(mutate(x, y = input[(days+1):nrow(input), "USD"]))
}

data.split <- function(data, ratio = 0.7) {
  n <- round(nrow(data) * ratio)
  train <- sample(1:nrow(data), n)
  test <- setdiff(1:nrow(data), train)
  return(list(data[train,], data[test,]))
}

train.glm <- function(data, horizon) {
  df <- forecast.horizon(days = horizon, input = data)
  spl <- data.split(df, ratio = 0.7)
  model.glm <- stepAIC(glm(formula = y ~ .,
                           data = spl[[1]],
                           family = 'gaussian'))
  return(list(model.glm, spl[[2]]))
}
```

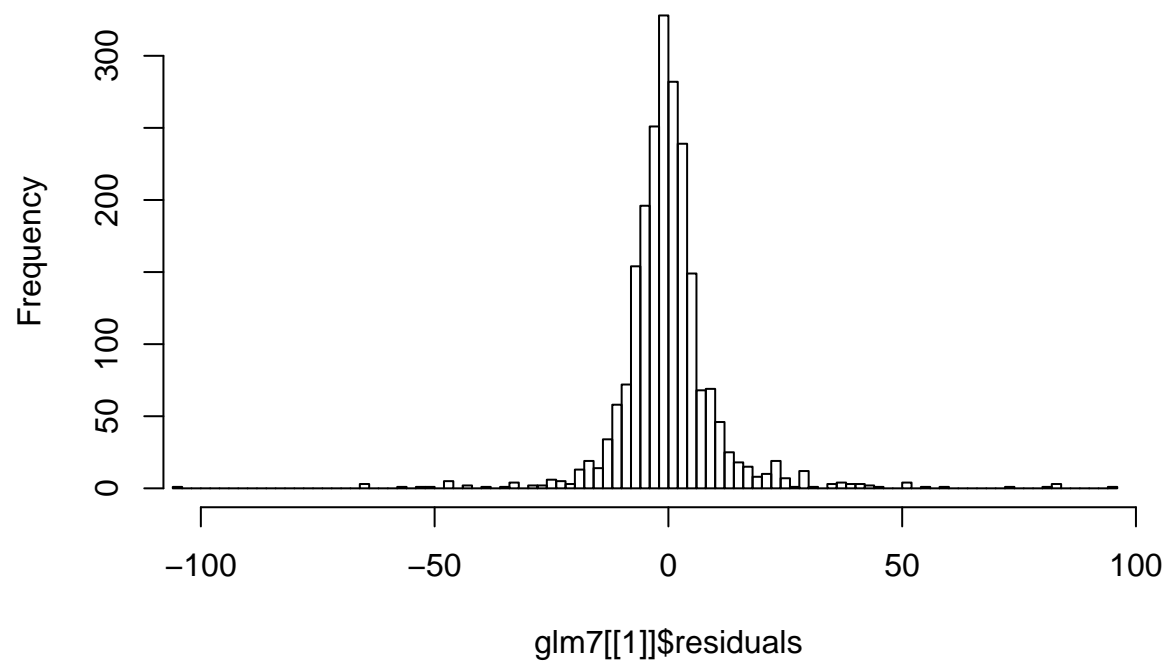
```
glm7 <- train.glm(rates, 7)
glm14 <- train.glm(rates, 14)
glm60 <- train.glm(rates, 60)
```

```
summary(glm7[[1]])
```

```
##      Length Class Mode
## [1,] 31      glm  list
```

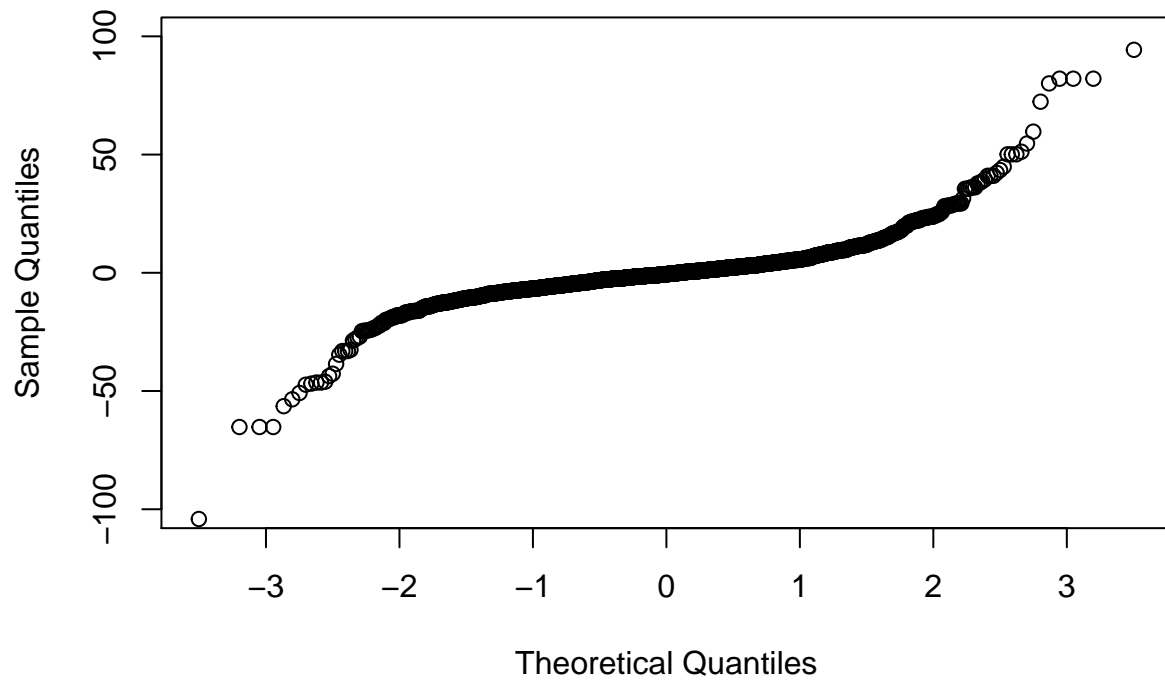
```
hist(glm7[[1]]$residuals, breaks = 100, xlim = c(-100, 100))
```

### Histogram of glm7[[1]]\$residuals



```
qqnorm(glm7[[1]]$residuals, ylim = c(-100, 100))
```

## Normal Q-Q Plot

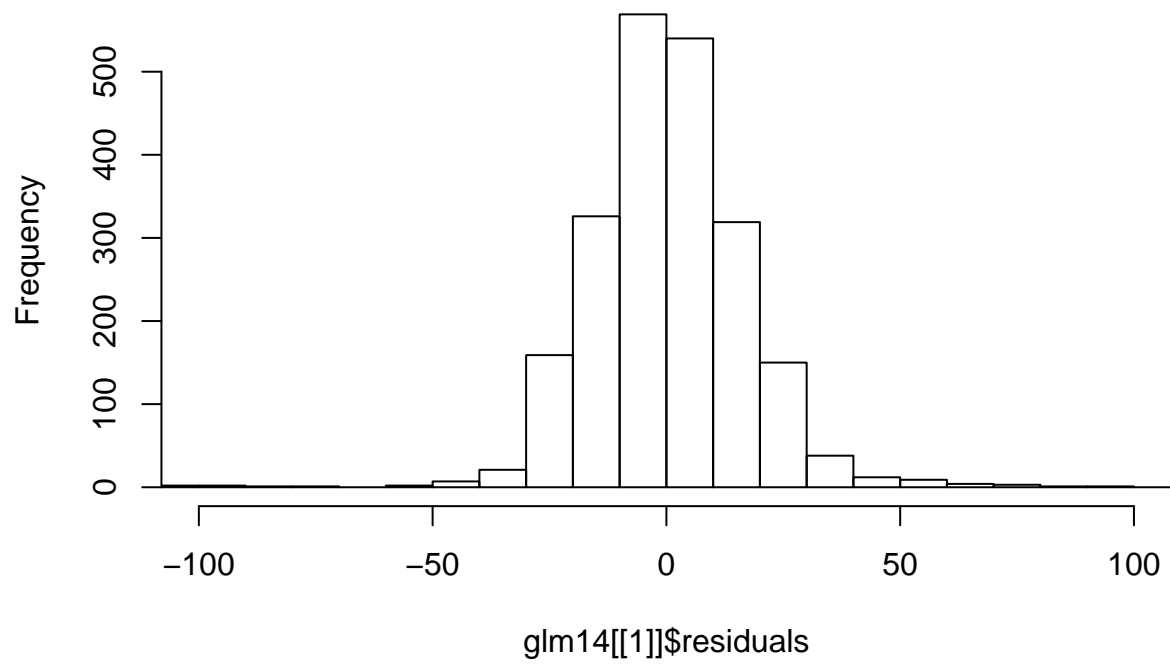


```
summary(glm14[1])
```

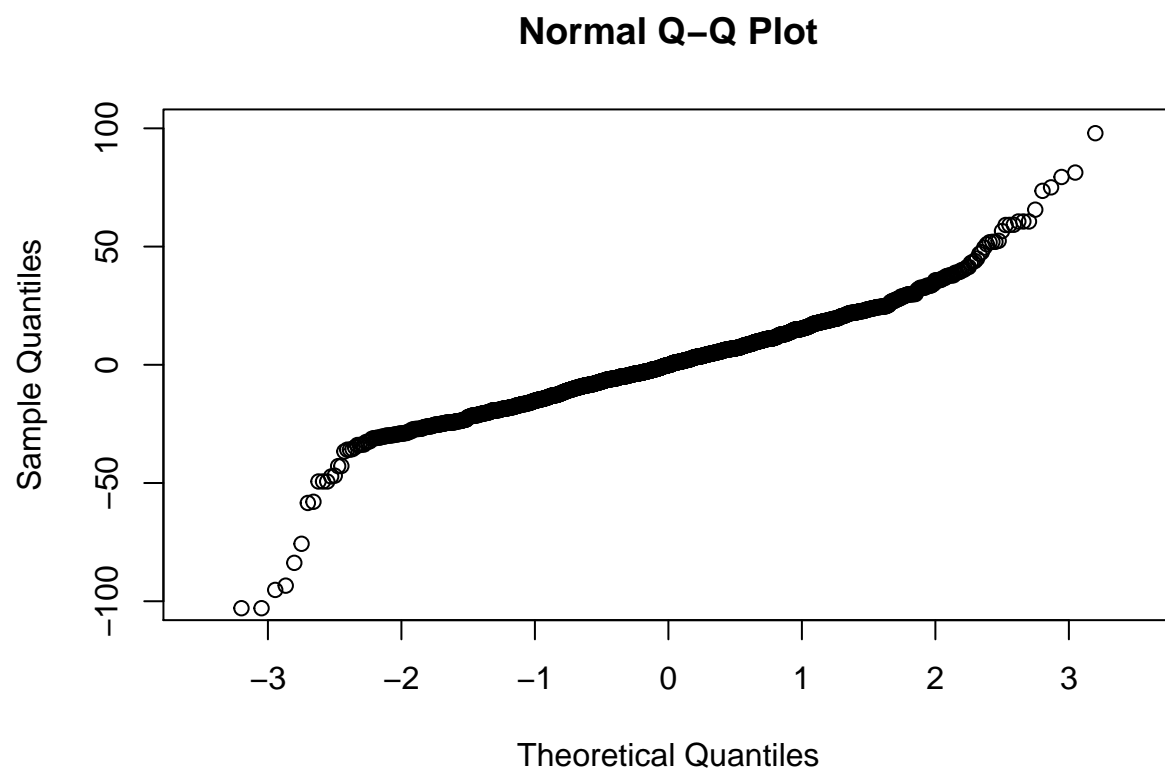
```
##      Length Class Mode  
## [1,] 31      glm    list
```

```
hist(glm14[[1]]$residuals, breaks = 100, xlim = c(-100, 100))
```

**Histogram of glm14[[1]]\$residuals**



```
qqnorm(glm14[[1]]$residuals, ylim = c(-100, 100))
```

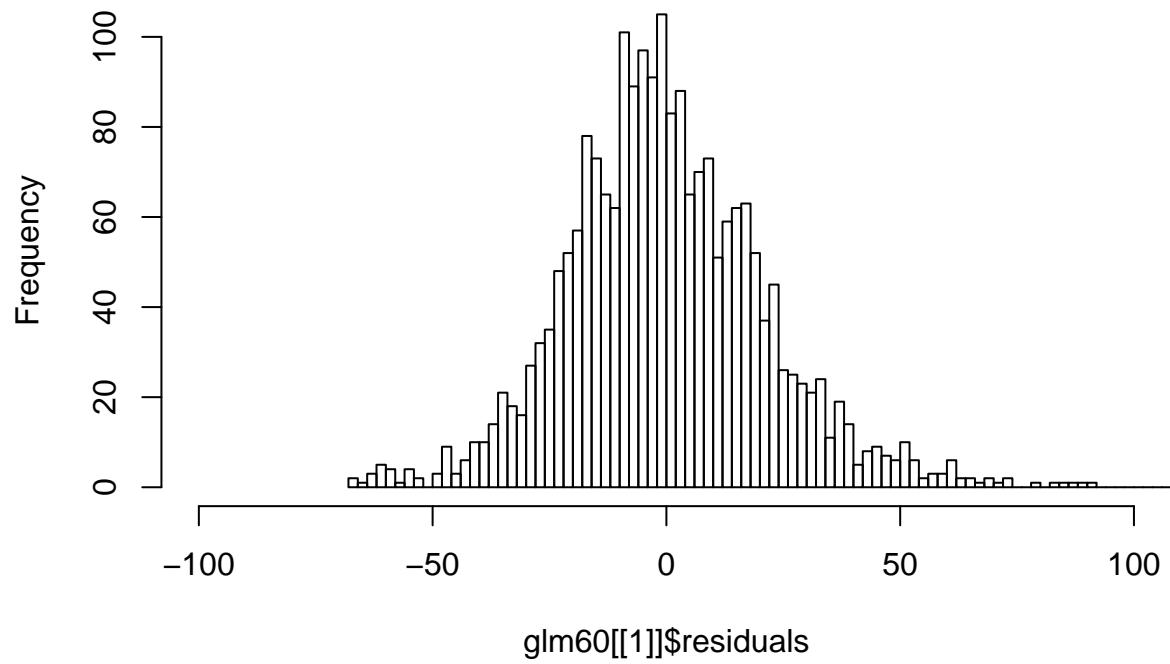


```
summary(glm60[1])
```

```
##      Length Class Mode  
## [1,] 31      glm  list
```

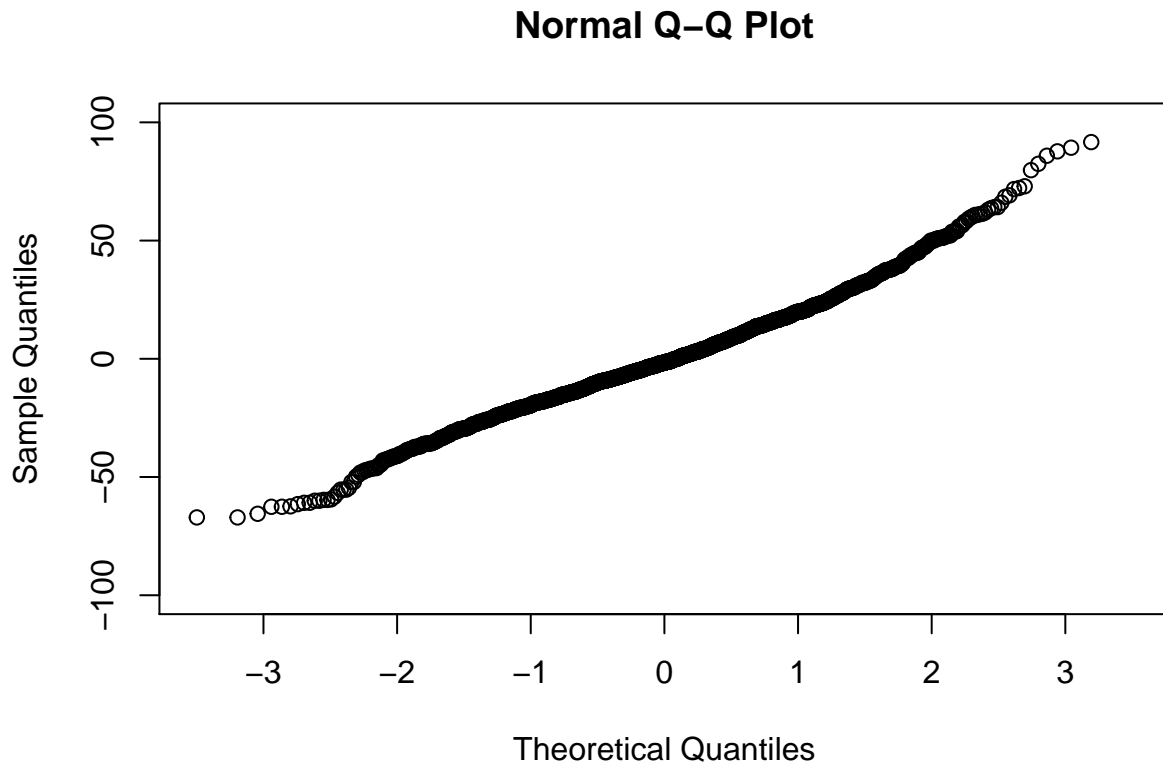
```
hist(glm60[[1]]$residuals, breaks = 100, xlim = c(-100, 100))
```

**Histogram of glm60[[1]]\$residuals**



```
qqnorm(glm60[[1]]$residuals, ylim = c(-100, 100))
```





### Interpreting the summaries...

Here we have 3 models based on prediction horizons of different values. The residuals of each model are centered around 0, and normally distributed with standard deviations that all appear lower than the smallest denomination of the currency, 50 kyats. Shorter predictions, understandably have errors centered more closely around zero, and longer ones exhibit more normal variance. There's really not a lot left to gain. But, we are predicting timeseries data with historical information? The typical wisdom suggests this shouldn't work. What's going on here?

This is not a free-floating currency! It isn't a monetary or inflationary target either, because the central bank doesn't have enough control over the money supply. There is a small committee who decides what the value of the kyat is going to be, and they don't make public their method of valuation. They introduce a small amount of randomness (and dispel many rumors about valuation by astrology) to discourage speculation in the market. However, a multiple regression model can cut right through, revealing the engineered value. I expect that the value is pegged to a weighted basket of currencies, and the results support this.

Our stepwise models reveal that previous relationships the 38 currencies can indicate the plans of the Central Bank of Myanmar. It would make sense that they cannot make huge corrections overnight (well, all the time), and these generalized models are able to pick up on these movements.

### Predicted Values

```
p7 <- predict.glm(glm7[[1]], glm7[[2]])  
p7b <- tibble(p7)
```

```

p7b$r <- names(p7)

p14 <- predict.glm(glm14[[1]], glm14[[2]])
p14b <- tibble(p14)
p14b$r <- names(p14)

p60 <- predict.glm(glm60[[1]], glm60[[2]])
p60b <- tibble(p60)
p60b$r <- names(p60)

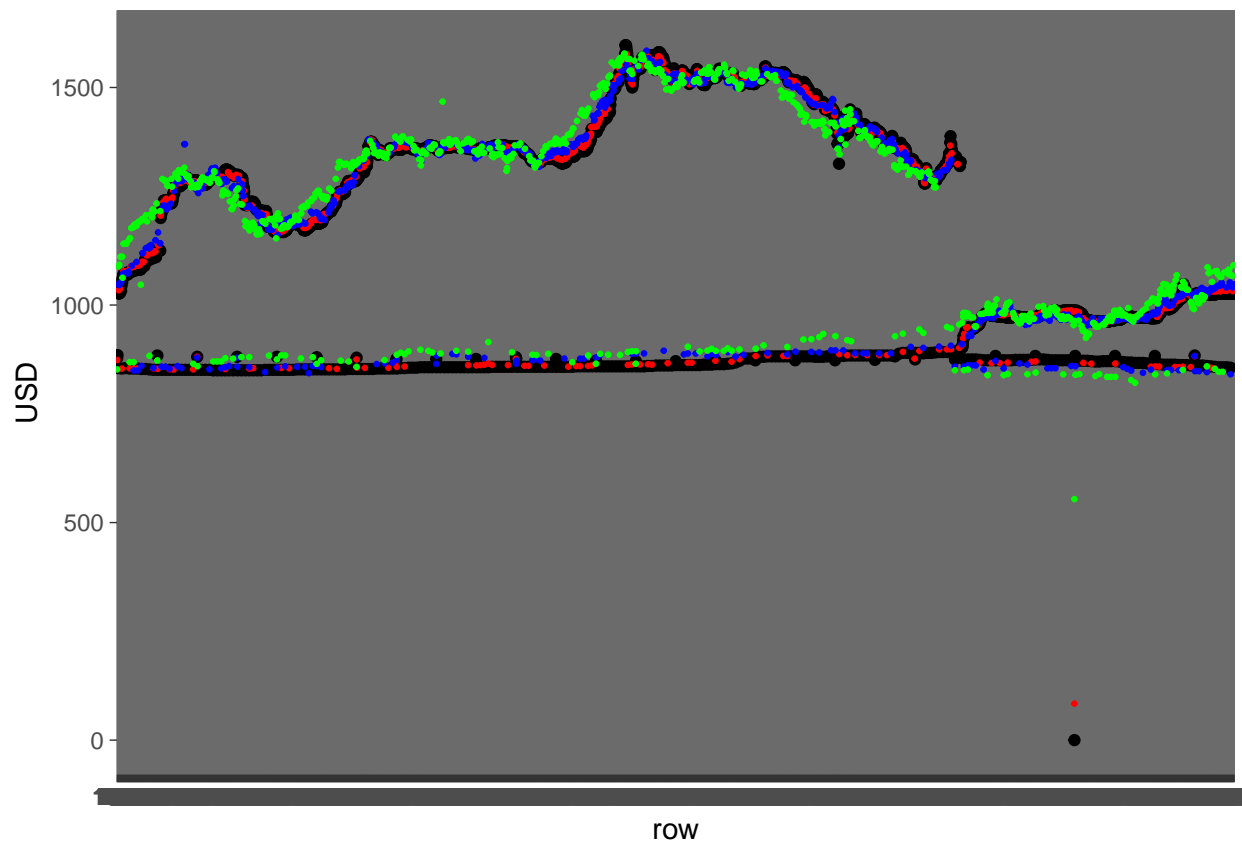
rates$row <- row.names(rates)

```

```

ggplot(rates, aes(x = row)) +
  geom_point(aes(y = USD)) +
  geom_point(data = p7b, aes(x = r, y = p7),
             size = 0.5, color = 'red') +
  geom_point(data = p14b, aes(x = r, y = p14),
             size = 0.5, color = 'blue') +
  geom_point(data = p60b, aes(x = r, y = p60),
             size = 0.5, color = 'green') +
  theme_dark()

```



Black dots are plotted first, the true values, and then red, blue, and green are laid on top: 7, 14, and 60 day horizon predictions. Each of the three models is a stepwise AIC chosen model, and they have slightly different sets of predictors. They also were trained off of different randomly sampled sets of 70% of the data.