# ARMA-X Analysis Tutorial

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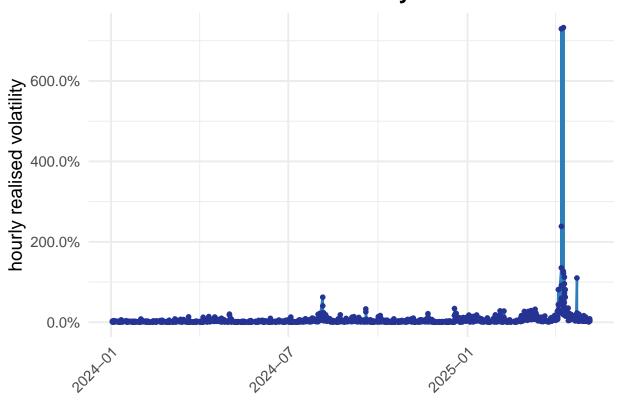
#### Data

#### Load Base Data

```
# 1. Load Political Social Media
#contains posts from Twitter & TruthSocial
social <- read.csv(here("data/mothership", "social.csv"))</pre>
social_hourly <- read.csv(here("data/mothership", "socialhourly.csv"))</pre>
# 2. Load Financial
#S&P500
SPY <- read.csv(here("data/mothership", "SPY.csv"))</pre>
#STOXX50
VGK <- read.csv(here("data/mothership", "VGK.csv"))</pre>
#CSI 300 (China)
ASHR <- read.csv(here("data/mothership", "ASHR.CSV"))
#make posixct
SPY$timestamp = as.POSIXct(SPY$timestamp,format = "%Y-%m-%d %H:%M:%S")
VGK$timestamp = as.POSIXct(VGK$timestamp,format = "%Y-%m-%d %H:%M:%S")
ASHR$timestamp = as.POSIXct(ASHR$timestamp,format = "%Y-%m-%d %H:%M:%S")
social$timestamp = as.POSIXct(social$timestamp,format = "%Y-%m-%d %H:%M:%S")
social_hourly$timestamp = as.POSIXct(social_hourly$timestamp,format = "%Y-%m-%d %H:%M:%S")
```

## Volatility

## Realised Volatility - SPY

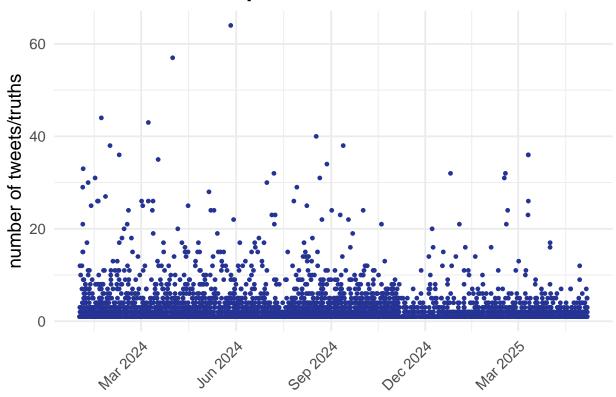


```
between(timestamp,
as.Date('2024-01-01'),
as.Date('2025-05-07')))
```

## **Number of Posts**

```
#find count
tweetcount_alltime = dplyr::select(social_hourly,timestamp,N)
#select time period
tweetcount = filter(tweetcount_alltime,
                  between(timestamp,
                          as.Date('2024-01-01'),
                          as.Date('2025-05-07')))
#plot
ggplot(tweetcount, aes(x = timestamp, y = N)) +
    geom_point(color = "#253494", size = 1) +
    scale_x_datetime(date_labels = "%b %Y", date_breaks = "3 month") +
    labs(title = "Trump Social Media Count",
         x = NULL,
        y = "number of tweets/truths") +
    theme_minimal(base_size = 14) +
    theme(axis.text.x = element_text(angle = 45, hjust = 1),
          plot.title = element_text(face = "bold", hjust = 0.5))
```

## **Trump Social Media Count**



## Dummy for Social Media Post

## Number of Tweets Mentioning Tariffs

### Number of Tweets Mentioning Trade

#### Proportion of Positive

### Proportion of Negative

#### Merge

```
#merge our dependant and independant vars
armax_data = left_join(SPY_volatility, VGK_volatility, by="timestamp")
armax_data = left_join(armax_data, ASHR_volatility, by="timestamp")
armax_data = left_join(armax_data, tweetdummy, by="timestamp")
armax_data = left_join(armax_data, tweetcount, by="timestamp")
armax_data = left_join(armax_data, tariff, by="timestamp")
armax_data = left_join(armax_data, trade, by="timestamp")
armax_data = left_join(armax_data, positive, by="timestamp")
armax_data = left_join(armax_data, negative, by="timestamp")
#rename volatility columns
names(armax_data)[2] <- "SPY_vol"</pre>
```

```
names(armax_data)[3] <- "VGK_vol"
names(armax_data)[4] <- "ASHR_vol"

#convert NA to zeroes
armax_data$N[is.na(armax_data$N)] = 0
armax_data$dummy[is.na(armax_data$dummy)] = 0
armax_data$total_tariff[is.na(armax_data$total_tariff)] = 0
armax_data$total_trade[is.na(armax_data$total_trade)] = 0
armax_data$prop_positive[is.na(armax_data$prop_positive)] = 0
armax_data$prop_negative[is.na(armax_data$prop_negative)] = 0</pre>
```

### S&P500 ARMA-X Tariff Models

## Finding Model

 $max_p = 7$ ,  $max_q = 7$ ,  $max_r = 3$ , criterion = "AIC", latex=T)

## Plotting IRFs

```
nb.periods = 20
irf.plot(res1,nb.periods)
```

	Model 1
ar1	0.9758***
	(0.0063)
ma1	$-0.6906^{***}$
	(0.0217)
ma2	-0.1800***
	(0.0214)
intercept	$0.0543^{*}$
	(0.0228)
$total\_tariff\_lag\_0$	-0.0066
	(0.0113)
$total\_tariff\_lag\_1$	-0.0131
	(0.0116)
$total\_tariff\_lag\_2$	$0.0359^{**}$
	(0.0117)
total_tariff_lag_3	-0.0049
	(0.0117)
total_tariff_lag_4	0.0044
	(0.0117)
total_tariff_lag_5	0.0037
	(0.0116)
total_tariff_lag_6	-0.0188
	(0.0115)
total_tariff_lag_7	-0.0141
	(0.0112)
AIC	-674.3212
AICc	-674.1655
BIC	-599.4019
Log Likelihood	350.1606
Num. obs.	2352

Table 1: ARMAX Model Results

	Model 1
ar1	0.3224***
	(0.0206)
ar2	0.0329
	(0.0219)
ar3	0.1113***
	(0.0224)
ar4	0.0896***
	(0.0223)
ar5	$0.0460^{*}$
	(0.0208)
intercept	$0.0539^{***}$
	(0.0110)
$total\_tariff\_lag\_0$	-0.0128
	(0.0115)
$total\_tariff\_lag\_1$	$-0.0250^{*}$
	(0.0122)
$total\_tariff\_lag\_2$	$0.0312^{**}$
	(0.0114)
AIC	-597.9298
AICc	-597.8360
BIC	-540.2783
Log Likelihood	308.9649
Num. obs.	2357
*** < 0.001 ** < 0.01 *	. 0.05

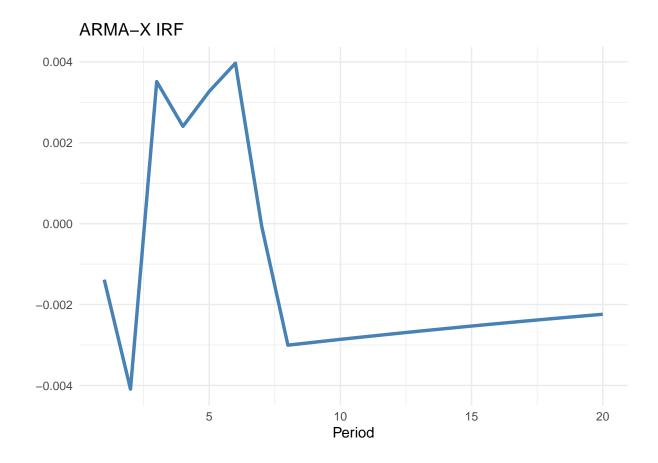
<sup>\*\*\*</sup>p < 0.001; \*\*p < 0.01; \*p < 0.05

Table 2: ARMAX Model Results

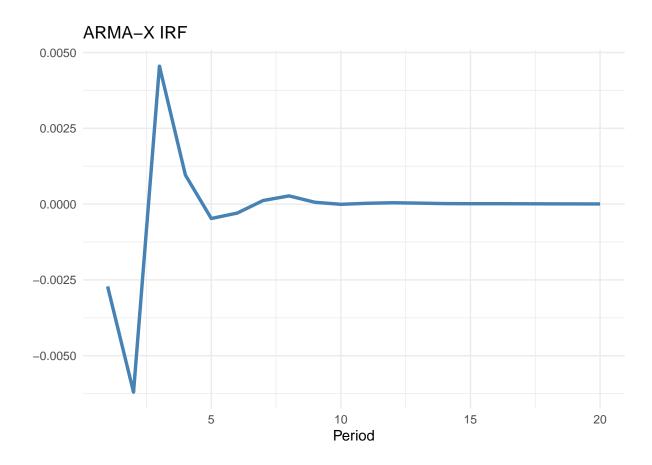
	Model 1
ar1	1.0801
ar2	-0.4288
ar3	0.4976***
ar4	(0.0488) $-0.3019***$
	(0.0281)
ar5	0.7924***
C	(0.0293)
ar6	$-0.6814^{***}$
ma1	(0.0150) $-0.7735***$
11141	(0.0094)
ma2	0.1292***
	(0.0303)
ma3	-0.3723***
	(0.0240)
ma4	0.2371***
	(0.0211)
ma5	$-0.9602^{***}$
	(0.0095)
ma6	0.6554
ma7	0.2287***
	(0.0181)
intercept	0.0507***
	(0.0138)
$total\_tariff\_lag\_0$	0.0030
	(0.0086)
$total\_tariff\_lag\_1$	-0.0101
	(0.0094)
$total\_tariff\_lag\_2$	0.0112
ATO	(0.0088)
AIC	-940.4859
AICc BIC	-940.1933 $-836.7133$
Log Likelihood	-830.7133 488.2429
Num. obs.	2357
*** $p < 0.001$ ; ** $p < 0.01$ ; * $p$	

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05

Table 3: ARMAX selected by AIC



irf.plot(res2,nb.periods)



irf.plot(res3\$model,nb.periods)

