# ARMA-X Analysis

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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

#find hourly volatility

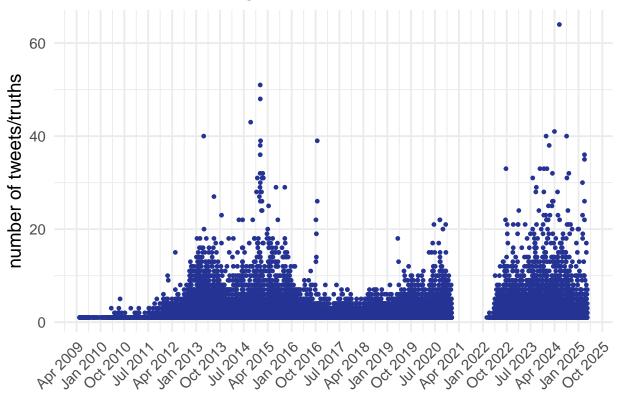
#NOTE: this ignores tweets made outside trading hours!!
VGK\_volatility\_alltime = dplyr::select(VGK,timestamp,r\_vol\_h)

#### Number of Posts

```
#find count
tweetcount_alltime = dplyr::select(social_hourly,timestamp,N)
#select time period
tweetcount = filter(tweetcount alltime,
                  between(timestamp,
                          as.Date('2014-01-01'),
                          as.Date('2025-04-10')))
#plot
ggplot(tweetcount_alltime, aes(x = timestamp, y = N)) +
    geom_point(color = "#253494", size = 1) +
    scale_x_datetime(date_labels = "%b %Y", date_breaks = "9 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))
```

## Warning: Removed 1172 rows containing missing values or values outside the scale range
## (`geom\_point()`).

## **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 Models

#### Find Number of Lags

Table 1:

	Table 1:	
	Depende	nt variable:
	y_8	aligned
	(no HAC)	(HAC)
	(1)	(2)
N_lag_0	-0.0005	$-0.0005^{***}$
	(0.0004)	(0.0002)
N_lag_1	-0.0001	-0.0001
	(0.0004)	(0.0002)
$N_{lag_2}$	0.0004	0.0004
	(0.0004)	(0.0003)
N_lag_3	0.0002	0.0002
0	(0.0004)	(0.0001)
$N_{lag_4}$	0.0004	0.0004
	(0.0004)	(0.0003)
N_lag_5	-0.0002	-0.0002
	(0.0004)	(0.0002)
Constant	0.022***	0.022***
	(0.001)	(0.001)
Observations	19,840	19,840
Note:	*p<0.1· **p<	0.05: ***p<0.0

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 2:

	$Dependent\ variable:$	
	y_a	ligned
	(no HAC)	(HAC)
	(1)	(2)
dummy_lag_0	-0.001	-0.001
	(0.001)	(0.002)
dummy_lag_1	-0.001	-0.001
	(0.001)	(0.001)
$dummy\_lag\_2$	0.004**	0.004**
	(0.001)	(0.002)
dummy_lag_3	$0.003^{*}$	$0.003^{**}$
	(0.001)	(0.001)
dummy_lag_4	$0.003^{*}$	0.003
	(0.001)	(0.002)
dummy_lag_5	-0.001	-0.001
	(0.001)	(0.001)
Constant	$0.020^{***}$	0.020***
	(0.001)	(0.001)
Observations	19,840	19,840

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 3:

	Dependent variable: y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
total_tariff_lag_0	0.036**	0.036
	(0.016)	(0.022)
total_tariff_lag_1	0.051***	0.051
<u> </u>	(0.016)	(0.038)
total_tariff_lag_2	0.045***	$0.045^{'}$
	(0.016)	(0.029)
total_tariff_lag_3	0.065***	$0.065^{**}$
	(0.016)	(0.029)
total_tariff_lag_4	0.066***	0.066**
	(0.016)	(0.031)
total tariff lag 5	0.085***	$0.085^{*}$
	(0.016)	(0.045)
Constant	0.021***	0.021***
	(0.001)	(0.001)
Observations	19,840	19,840

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 4:

	Dependent variable:	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
total_trade_lag_0	-0.003	-0.003
	(0.008)	(0.004)
$total\_trade\_lag\_1$	0.002	0.002
	(0.008)	(0.008)
$total\_trade\_lag\_2$	-0.001	-0.001
	(0.008)	(0.005)
$total\_trade\_lag\_3$	0.001	0.001
	(0.008)	(0.006)
$total\_trade\_lag\_4$	-0.001	-0.001
	(0.008)	(0.006)
$total\_trade\_lag\_5$	-0.002	-0.002
	(0.008)	(0.005)
Constant	$0.022^{***}$	$0.022^{***}$
	(0.001)	(0.001)
Observations	19,840	19,840
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5:

	Dependent variable: y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
prop_positive_lag_0	0.0004	0.0004
	(0.002)	(0.004)
prop_positive_lag_1	-0.0004	-0.0004
	(0.002)	(0.001)
prop_positive_lag_2	0.008***	0.008*
	(0.002)	(0.004)
prop_positive_lag_3	0.002	0.002
	(0.002)	(0.002)
prop_positive_lag_4	0.005**	0.005
	(0.002)	(0.004)
prop_positive_lag_5	-0.001	-0.001
	(0.002)	(0.001)
Constant	0.020***	0.020***
	(0.001)	(0.001)
Observations	19,840	19,840
Note:	*p<0.1; **p<	0.05; ***p<0

Table 6:

	Dependent variable:	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
prop_negative_lag_0	-0.002	-0.002
	(0.003)	(0.002)
$prop\_negative\_lag\_1$	-0.002	-0.002
	(0.003)	(0.002)
$prop\_negative\_lag\_2$	0.001	0.001
	(0.003)	(0.001)
prop_negative_lag_3	0.007**	0.007
	(0.003)	(0.006)
prop_negative_lag_4	0.002	0.002
	(0.003)	(0.002)
prop_negative_lag_5	-0.002	-0.002
	(0.003)	(0.002)
Constant	0.021***	$0.021^{***}$
	(0.001)	(0.001)
Observations	19,840	19,840
Note:	*p<0.1; **p<0.05; ***p<0.01	

## Tweet Count on Volatility by hour

```
armax(armax_data$SPY_vol,xreg=armax_data$N,nb.lags=0,latex=T)
```

### Tweet Dummy on Volatility by hour

```
armax(armax_data$SPY_vol,xreg=armax_data$dummy,nb.lags=3,latex=T)
```

## Tariff Mention on Volatility by hour

```
armax(armax_data$SPY_vol,xreg=armax_data$total_tariff,nb.lags=5,latex=T)
```

## Positive Vibe on Volatility by hour

```
armax(armax_data$SPY_vol,xreg=armax_data$prop_positive,nb.lags=2,latex=T)
```

	Model 1
ar1	0.3478***
	(0.0071)
ar2	0.0345***
	(0.0076)
ar3	$0.0825^{***}$
	(0.0101)
ar4	$0.1541^{***}$
	(0.0106)
ar5	0.1050***
	(0.0095)
intercept	0.0222***
	(0.0020)
$N_{lag}0$	-0.0005
	(0.0003)
AIC	-44843.0497
AICc	-44843.0424
BIC	-44779.8840
Log Likelihood	22429.5248
Num. obs.	19845
***n < 0.001 · **n < 0.0	$0.1 \cdot *n < 0.05$

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

Table 7: ARMAX Model Results

	Model 1
ar1	0.3476***
	(0.0071)
ar2	0.0344***
	(0.0076)
ar3	$0.0835^{***}$
	(0.0101)
ar4	$0.1542^{***}$
	(0.0106)
ar5	$0.1045^{***}$
	(0.0095)
intercept	0.0209***
	(0.0022)
$dummy\_lag\_0$	-0.0016
	(0.0012)
$dummy\_lag\_1$	-0.0010
	(0.0012)
$dummy\_lag\_2$	0.0038**
	(0.0012)
$dummy\_lag\_3$	0.0022
	(0.0012)
AIC	-44839.4930
AICc	-44839.4797
BIC	-44752.6419
Log Likelihood	22430.7465
Num. obs.	19842
*** $p < 0.001$ : *** $p < 0.0$	01: *p < 0.05

p < 0.001; p < 0.01; p < 0.01; p < 0.05

Table 8: ARMAX Model Results

	Model 1
ar1	0.3471***
	(0.0071)
ar2	0.0359***
	(0.0076)
ar3	0.0822***
	(0.0102)
ar4	0.1564***
	(0.0109)
ar5	0.1083***
	(0.0098)
intercept	0.0222***
	(0.0021)
$total\_tariff\_lag\_0$	-0.0422**
_	(0.0142)
total_tariff_lag_1	-0.0288
_	(0.0147)
$total\_tariff\_lag\_2$	-0.0480***
	(0.0145)
$total\_tariff\_lag\_3$	$-0.0319^*$
	(0.0146)
$total\_tariff\_lag\_4$	$-0.0383^*$
	(0.0149)
$total\_tariff\_lag\_5$	-0.0153
	(0.0144)
AIC	-44836.1606
AICc	-44836.1423
BIC	-44733.5197
Log Likelihood	22431.0803
Num. obs.	19840
*** $p < 0.001$ ; ** $p < 0.01$ ; * $p < 0.01$ ;	0 < 0.05

Table 9: ARMAX Model Results

	Model 1
ar1	0.3481***
	(0.0071)
ar2	$0.0338^{***}$
	(0.0076)
ar3	$0.0835^{***}$
	(0.0101)
ar4	0.1539***
	(0.0106)
ar5	0.1048***
	(0.0095)
intercept	0.0212***
	(0.0021)
$prop\_positive\_lag\_0$	-0.0018
	(0.0018)
$prop\_positive\_lag\_1$	-0.0013
	(0.0018)
prop_positive_lag_2	$0.0074^{***}$
	(0.0018)
AIC	-44849.0130
AICc	-44849.0019
BIC	-44770.0570
Log Likelihood	22434.5065
Num. obs.	19843

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

Table 10: ARMAX Model Results

## European Market ARMA-X Models

### Find Number of Lags

Table 11:

	Table 11:	
	Depender	nt variable:
	y_a	ligned
	(no HAC)	(HAC)
	(1)	(2)
N_lag_0	$-0.00001^{**}$	$-0.00001^{***}$
-	(0.00001)	(0.00000)
N_lag_1	-0.00000	-0.00000
	(0.00001)	(0.00000)
$N_{lag_2}$	0.00000	0.00000
	(0.00001)	(0.00000)
N_lag_3	0.00000	0.00000
_	(0.00001)	(0.00000)
N_lag_4	0.00000	0.00000
_	(0.00001)	(0.00000)
N_lag_5	-0.00000	-0.00000
_ 0_	(0.00001)	(0.00000)
Constant	0.0004***	0.0004***
	(0.00002)	(0.00002)
Observations	19,799	19,799
Note:	*p<0.1; **p<	0.05; ***p<0.01

Table 12:

	$\underline{\hspace{2cm}} Dependent\ variable:$	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
dummy_lag_0	$-0.0001^*$	$-0.0001^*$
	(0.00003)	(0.00003)
dummy_lag_1	-0.00001	-0.00001
	(0.00003)	(0.00002)
dummy_lag_2	0.00002	0.00002
	(0.00003)	(0.00003)
dummy_lag_3	0.0001**	0.0001**
	(0.00003)	(0.00003)
dummy_lag_4	0.00001	0.00001
	(0.00003)	(0.00002)
dummy_lag_5	-0.00002	-0.00002
	(0.00003)	(0.00003)
Constant	0.0004***	$0.0004^{***}$
	(0.00002)	(0.00002)
Observations	19,799	19,799
Motor	*n <0 1. **n <0 05. ***n <0 01	

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 13:

	10010 10.	
	Dependent variable: y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
total_tariff_lag_0	0.0001	0.0001
	(0.0003)	(0.0002)
total_tariff_lag_1	0.0003	0.0003
_	(0.0003)	(0.0003)
total_tariff_lag_2	0.0002	0.0002
	(0.0003)	(0.0002)
total_tariff_lag_3	0.0003	0.0003
	(0.0003)	(0.0002)
total_tariff_lag_4	0.0004	$0.0004^{*}$
	(0.0003)	(0.0002)
total_tariff_lag_5	0.0004	$0.0004^{*}$
	(0.0003)	(0.0002)
Constant	0.0004***	0.0004***
	(0.00001)	(0.00002)
Observations	19,799	19,799

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 14:

	Dependent variable: y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
otal_trade_lag_0	-0.0001	-0.0001
	(0.0002)	(0.00004)
$otal\_trade\_lag\_1$	-0.00004	-0.00004
	(0.0002)	(0.0001)
$otal\_trade\_lag\_2$	-0.00000	-0.00000
	(0.0002)	(0.0001)
$otal\_trade\_lag\_3$	-0.00004	-0.00004
	(0.0002)	(0.00004)
$otal\_trade\_lag\_4$	-0.00003	-0.00003
	(0.0002)	(0.00004)
$otal\_trade\_lag\_5$	-0.00000	-0.00000
	(0.0002)	(0.0001)
Constant	0.0004***	0.0004***
	(0.00001)	(0.00002)
Observations	19,799	19,799
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 15:

	(no HAC)	(HAC)
	(1)	(2)
prop_positive_lag_0	-0.00002	-0.00002
	(0.00004)	(0.0001)
prop_positive_lag_1	-0.00001	-0.00001
	(0.00004)	(0.00003)
prop_positive_lag_2	0.00003	0.00003
	(0.00004)	(0.00005)
prop_positive_lag_3	0.0001	0.0001
	(0.00004)	(0.00004)
prop_positive_lag_4	0.00004	0.00004
	(0.00004)	(0.00004)
prop_positive_lag_5	-0.0001	$-0.0001^*$
	(0.00004)	(0.00003)
Constant	0.0004***	0.0004***
	(0.00002)	(0.00002)
Observations	19,799	19,799
Note:	*p<0.1; **p<	0.05; ***p<0

Table 16:

	(no HAC)	(HAC)
	(1)	(2)
prop_negative_lag_0	-0.0001**	-0.0001***
	(0.0001)	(0.00003)
prop_negative_lag_1	-0.0001	-0.0001
	(0.0001)	(0.00004)
prop_negative_lag_2	-0.00000	-0.00000
	(0.0001)	(0.00005)
prop_negative_lag_3	0.0001*	0.0001
	(0.0001)	(0.0001)
prop_negative_lag_4	-0.00002	-0.00002
	(0.0001)	(0.00003)
prop_negative_lag_5	0.00004	0.00004
	(0.0001)	(0.0001)
Constant	0.0004***	0.0004***
	(0.00002)	(0.00002)
Observations	19,799	19,799
Note:	*p<0.1; **p<	(0.05; ***p<0.01

p<0.1; ~p<0.05; ~p<0.01

## Tweet Count on Volatility by hour

```
armax(armax_data$VGK_vol,xreg=armax_data$N,nb.lags=0,latex=T)
```

### Tweet Dummy on Volatility by hour

```
armax(armax_data$VGK_vol,xreg=armax_data$dummy,nb.lags=3,latex=T)
```

## Tariff Mention on Volatility by hour

```
armax(armax_data$VGK_vol,xreg=armax_data$total_tariff,nb.lags=5,latex=T)
```

## Negative Vibe on Volatility by hour

```
armax(armax_data$VGK_vol,xreg=armax_data$prop_negative,nb.lags=0,latex=T)
```

	Model 1
ar1	1.3706***
	(0.0103)
ar2	-0.4744***
	(0.0146)
ar3	$0.0946^{***}$
	(0.0084)
ma1	$-0.9571^{***}$
	(0.0049)
intercept	$0.0004^{***}$
	(0.0001)
$N_{lag}0$	-0.0000
	(0.0000)
AIC	-199309.4472
AICc	-199309.4416
BIC	-199254.1918
Log Likelihood	99661.7236
Num. obs.	19804
*** $p < 0.001$ ; ** $p < 0.00$	01; *p < 0.05

Table 17: ARMAX Model Results

	Model 1
ar1	1.3711***
	(0.0103)
ar2	$-0.4741^{***}$
	(0.0146)
ar3	0.0941***
	(0.0084)
ma1	$-0.9580^{***}$
	(0.0048)
intercept	0.0004***
	(0.0001)
$dummy_lag_0$	-0.0000
	(0.0000)
$dummy_lag_1$	-0.0000
	(0.0000)
$dummy\_lag\_2$	0.0000
	(0.0000)
$dummy\_lag\_3$	0.0001*
	(0.0000)
AIC	-199276.6568
AICc	-199276.6457
BIC	-199197.7219
Log Likelihood	99648.3284
Num. obs.	19801
***. < 0.001 ** < 0.0	24 *

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

Table 18: ARMAX Model Results

	Model 1
ar1	0.9891***
	(0.0023)
ma1	-0.5735***
	(0.0095)
ma2	$-0.3191^{***}$
	(0.0104)
ma3	-0.0526***
	(0.0091)
intercept	0.0004***
	(0.0001)
$total\_tariff\_lag\_0$	-0.0003
	(0.0003)
$total\_tariff\_lag\_1$	-0.0002
	(0.0003)
$total\_tariff\_lag\_2$	-0.0002
	(0.0003)
$total\_tariff\_lag\_3$	-0.0002
	(0.0003)
$total\_tariff\_lag\_4$	-0.0001
	(0.0003)
$total\_tariff\_lag\_5$	-0.0000
	(0.0003)
AIC	-199243.6740
AICc	-199243.6582
BIC	-199148.9534
Log Likelihood	99633.8370
Num. obs.	19799
*** < 0.001. ** < 0.01. *-	0.0F

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

Table 19: ARMAX Model Results

Model 1
0.9886***
(0.0024)
-0.5728***
(0.0096)
-0.3192***
(0.0103)
-0.0524****
(0.0091)
0.0004***
(0.0001)
-0.0001
(0.0000)
-199309.9660
-199309.9603
-199254.7105
99661.9830
19804

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

Table 20: ARMAX Model Results

### Chinese Market ARMA-X Models

#### Find Number of Lags

Table 21:

	Table 21.	
	Dependent variable:	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
N_lag_0	$-0.00001^{***}$	-0.00001***
	(0.00000)	(0.00000)
N_lag_1	0.00000	0.00000
	(0.00000)	(0.00000)
N_lag_2	0.00000	0.00000
	(0.00000)	(0.00000)
N_lag_3	0.00000**	0.00000***
_ 0_	(0.00000)	(0.00000)
N_lag_4	$0.00000^{*}$	$0.00000^{*}$
_ 0_	(0.00000)	(0.00000)
N_lag_5	-0.00000	-0.00000**
8	(0.00000)	(0.00000)
Constant	0.0002***	0.0002***
	(0.00000)	(0.00001)
Observations	19,782	19,782
Note:	*p<0.1; **p<0	0.05; ***p<0.01

Note: "p<0.1; "p<0.05; "p<0.01

Table 22:

	Dependent variable:	
	$y\_aligned$	
	(no HAC)	(HAC)
	(1)	(2)
dummy_lag_0	$-0.00004^{***}$	-0.00004***
	(0.00001)	(0.00001)
dummy_lag_1	0.00003***	0.00003***
	(0.00001)	(0.00001)
$dummy_lag_2$	0.00002**	0.00002***
	(0.00001)	(0.00001)
dummy_lag_3	0.00004***	0.00004***
	(0.00001)	(0.00001)
$dummy_lag_4$	0.00001	0.00001
	(0.00001)	(0.00001)
dummy_lag_5	$-0.00001^*$	-0.00001**
	(0.00001)	(0.00001)
Constant	0.0002***	0.0002***
	(0.00001)	(0.00001)
Observations	19,782	19,782
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 23:

	(no HAC)	(HAC)
	(1)	(2)
total_tariff_lag_0	-0.0001	-0.0001***
	(0.0001)	(0.00002)
total_tariff_lag_1	-0.00004	-0.00004
_	(0.0001)	(0.00003)
total_tariff_lag_2	-0.0001	-0.0001**
	(0.0001)	(0.00001)
total_tariff_lag_3	-0.0001	-0.0001**
	(0.0001)	(0.00001)
total_tariff_lag_4	-0.0001	-0.0001**
_	(0.0001)	(0.00002)
total_tariff_lag_5	-0.00005	$-0.00005^*$
_	(0.0001)	(0.00003)
Constant	0.0002***	0.0002***
	(0.00000)	(0.00001)
Observations	19,782	19,782
Notes	*n/0.1· **n/0.05· ***n/0.01	

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 24:

	Dependent variable:	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
total_trade_lag_0	-0.00001	-0.00001
	(0.00004)	(0.00002)
$total\_trade\_lag\_1$	-0.00003	-0.00003
	(0.00004)	(0.00002)
$total\_trade\_lag\_2$	0.0003***	0.0003
	(0.00004)	(0.0003)
total_trade_lag_3	0.0001*	0.0001
	(0.00004)	(0.00005)
total_trade_lag_4	0.0001***	0.0001
	(0.00004)	(0.0001)
total_trade_lag_5	0.00003	0.00003
	(0.00004)	(0.00003)
Constant	0.0002***	0.0002***
	(0.00000)	(0.00001)
Observations	19,782	19,782
Note:	*p<0.1; **p<	0.05; ***p<0.01

Table 25:

	Dependen	t variable:
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
prop_positive_lag_0	$-0.00003^{***}$	-0.00003**
	(0.00001)	(0.00001)
prop_positive_lag_1	0.00004***	0.00004***
	(0.00001)	(0.00001)
prop_positive_lag_2	0.00003***	0.00003***
	(0.00001)	(0.00001)
prop_positive_lag_3	0.0001***	0.0001***
	(0.00001)	(0.00001)
prop_positive_lag_4	0.00001	0.00001
	(0.00001)	(0.00001)
prop_positive_lag_5	-0.00000	-0.00000
	(0.00001)	(0.00001)
Constant	0.0001***	0.0001***
	(0.00000)	(0.00001)
Observations	19,782	19,782
Note:	*p<0.1; **p<0	0.05; ***p<0.0

Table 26:

	Dependent variable:	
	y_aligned	
	(no HAC)	(HAC)
	(1)	(2)
prop_negative_lag_0	$-0.0001^{***}$	-0.0001***
	(0.00001)	(0.00001)
prop_negative_lag_1	-0.00001	-0.00001
	(0.00001)	(0.00001)
$prop\_negative\_lag\_2$	-0.00000	-0.00000
	(0.00001)	(0.00001)
prop_negative_lag_3	0.00002	0.00002
	(0.00001)	(0.00001)
prop_negative_lag_4	-0.00001	-0.00001
	(0.00001)	(0.00001)
prop_negative_lag_5	-0.00005***	$-0.00005^{***}$
	(0.00001)	(0.00001)
Constant	0.0002***	0.0002***
	(0.00000)	(0.00001)
Observations	19,782	19,782
Note:	*p<0.1; **p<0	.05; ***p<0.01

## Tweet Count on Volatility by hour

```
armax(armax_data$ASHR_vol,xreg=armax_data$N,nb.lags=5,latex=T)
```

### Tweet Dummy on Volatility by hour

```
armax(armax_data$ASHR_vol,xreg=armax_data$dummy,nb.lags=5,latex=T)
```

## Tariff Mention on Volatility by hour

```
armax(armax_data$ASHR_vol,xreg=armax_data$total_tariff,nb.lags=5,latex=T)
```

## Positive Vibe on Volatility by hour

```
armax(armax_data$ASHR_vol,xreg=armax_data$prop_positive,nb.lags=3,latex=T)
```

	Model 1
ar1	0.9869***
	(0.0021)
ma1	$-0.8890^{***}$
	(0.0071)
$N_{lag}0$	-0.0000
	(0.0000)
$N_{lag_1}$	0.0000
	(0.0000)
$N_{lag_2}$	0.0000
	(0.0000)
$N_{lag_3}$	0.0000
	(0.0000)
$N_{lag_4}$	0.0000
	(0.0000)
$N_{lag_5}$	-0.0000
	(0.0000)
AIC	-252815.6654
AICc	-252815.6563
BIC	-252744.6326
Log Likelihood	126416.8327
Num. obs.	19782
*** $p < 0.001$ ; *** $p < 0.01$ ; * $p < 0.05$	

 $^*p < 0.001; \ ^{**}p < 0.01; \ ^*p < 0.05$ 

Table 27: ARMAX Model Results

## Negative Vibe on Volatility by hour

armax(armax\_data\$ASHR\_vol,xreg=armax\_data\$prop\_negative,nb.lags=5,latex=T)

	Model 1
ar1	0.9900***
	(0.0015)
ma1	$-0.7428^{***}$
	(0.0072)
ma2	$-0.1820^{***}$
	(0.0072)
intercept	0.0001***
	(0.0000)
$dummy\_lag\_0$	-0.0000***
	(0.0000)
$dummy\_lag\_1$	$0.0000^{**}$
	(0.0000)
$dummy\_lag\_2$	0.0000
	(0.0000)
$dummy\_lag\_3$	0.0000***
	(0.0000)
$dummy\_lag\_4$	0.0000
	(0.0000)
$dummy\_lag\_5$	-0.0000
	(0.0000)
AIC	-253562.5355
AICc	-253562.5222
BIC	-253475.7177
Log Likelihood	126792.2678
Num. obs.	19782
*** $p < 0.001$ ; ** $p < 0.001$	01; *p < 0.05

p < 0.001; p < 0.01; p < 0.01; p < 0.05

Table 28: ARMAX Model Results

	Model 1
ar1	0.9730***
	(0.0035)
ma1	$-0.8650^{***}$
	(0.0091)
intercept	0.0002***
	(0.0000)
$total\_tariff\_lag\_0$	-0.0001
	(0.0001)
total_tariff_lag_1	-0.0000
	(0.0001)
total tariff lag 2	-0.0001
	(0.0001)
total_tariff_lag_3	-0.0001
	(0.0001)
total_tariff_lag_4	-0.0000
	(0.0001)
total_tariff_lag_5	-0.0000
	(0.0001)
AIC	-252847.8136
AICc	-252847.8025
BIC	-252768.8884
Log Likelihood	126433.9068
Num. obs.	19782

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

Table 29: ARMAX Model Results

	Model 1	
ar1	0.0685	
	(0.0562)	
ar2	0.9124***	
	(0.0557)	
ma1	0.1792**	
	(0.0568)	
ma2	-0.8724***	
	(0.0413)	
ma3	-0.1626***	
	(0.0133)	
intercept	0.0002***	
	(0.0000)	
prop_positive_lag_0	-0.0000****	
	(0.0000)	
prop_positive_lag_1	0.0000*	
	(0.0000)	
prop_positive_lag_2	0.0000*	
	(0.0000)	
prop_positive_lag_3	0.0000***	
	(0.0000)	
AIC	-253551.1009	
AICc	-253551.0875	
BIC	-253464.2820	
Log Likelihood	126786.5504	
Num. obs.	19784	
*** .0.001 ** .0.01 * .0.05		

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

Table 30: ARMAX Model Results

	Model 1
ar1	0.9730***
	(0.0035)
ma1	$-0.8645^{***}$
	(0.0091)
intercept	$0.0002^{***}$
	(0.0000)
$prop\_negative\_lag\_0$	-0.0001***
	(0.0000)
$prop\_negative\_lag\_1$	0.0000
	(0.0000)
$prop\_negative\_lag\_2$	0.0000
	(0.0000)
$prop\_negative\_lag\_3$	0.0000**
	(0.0000)
$prop\_negative\_lag\_4$	0.0000
	(0.0000)
$prop\_negative\_lag\_5$	-0.0000
	(0.0000)
AIC	-252890.7623
AICc	-252890.7511
BIC	-252811.8370
Log Likelihood	126455.3811
Num. obs.	19782

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

Table 31: ARMAX Model Results