The Art of the Tweet: Do Trump's Posts Affect Market Volatility?

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Abstract

In this short paper, we aim to asses to what extent financial markets may react to Donald Trump's social media posts, and more specifically, the effect on average realised volatility. We do so using both ARMA-X and SVAR models, with data spanning the 1st of January 2014, to the 7th of May 2025, over various time horizons and independent variables. Being limited by persistent auto-correlation in the residuals, we find limited evidence that there is a statistically significant positive effect, and provide some explanations as to why this might be the case.

Contents

1 Introduction

1.1 Motivation

Over the past 15 years, social media has become an important communication tool for politicians. One of the pioneers of this novel approach has been Donald Trump, the 45th and 47th President of the United States. Since his ban on Twitter after the January 6th riots, his quantity of social media posts has drastically increased to absurd levels as clearly visible on Figure 1.

The content of his posts can sometimes have announcements or teases of future political decisions. Note the recent infamous "THIS IS A GREAT TIME TO BUY!!! DJT" post sent just an hour before lifting his reciprocal tariffs. It is then not improbable that agents in financial markets might take this information into account in their decision making. This question has been asked before in the literature, focusing rather on his first term.

This brings us to our research question: Do Donald Trump's Posts impact market Volatility?

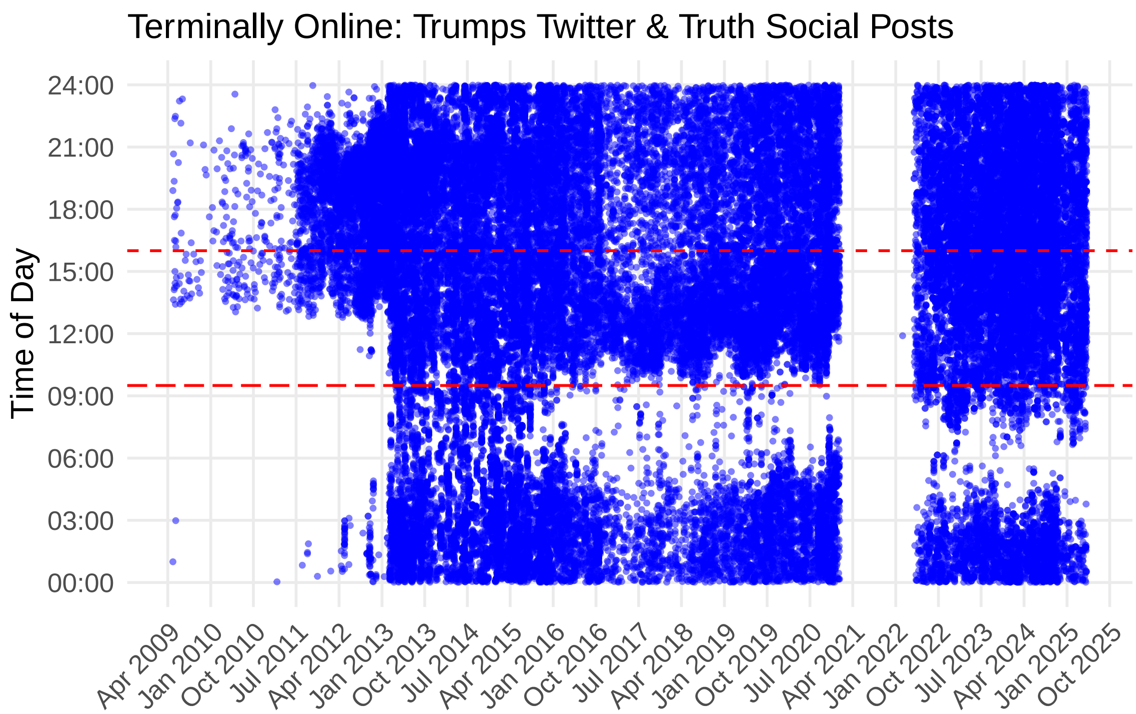

Figure 1: Number of Twitter & Truth Social Posts (EDT Timezone)

1.2 Literature Review

Information is one of the most valuable assets in the financial market. Its importance lies at the core of the "Efficient Market Hypothesis", which states that the prices of assets fully reflect all available information, adjusting immediately to any new data (Fama et al. (2003)) , and thereby creating a strong demand for information flow. In addition, the "Mixture of Distribution Hypothesis" states that the release of new information is closely linked to movements in both realized and implied volatility (Andersen (1996), French & Roll (1986), Vlastakis & Markellos (2012)).

Consequently, a large part of the literature has focused on the relation between announcements, news and market activity. For example, Schumaker & Chen (2009) use various linguistic and textual representations derived from financial news to predict stock market prices. Similarly, Ederington & Lee (1993) analyze the impact of macroeconomic news announcements on interest rate and foreign exchange futures markets, particularly in terms of price changes and volatility. Both studies, among others, find that prices, such as stock prices, react primarily within minutes after the release of new information.

Recently, the world has witnessed the rise of the Internet which revolutionized the dissemination and accessibility of information. Social media enables investors, analysts or politicians to instantly share their information, news or opinions.

This led some studies to focus on the communication dynamics of social platforms to predict changes in the returns of financial assets (De Choudhury et al. (2008) and Bartov et al. (2018)). In this context, the impact of Trump's tweets on various financial and macroeconomic variables has been analysed by several studies, especially during his first mandate.

Using high-frequency financial data, Gjerstad et al. (2021) found consistent increases in uncertainty and trading volume, along with a decline in the U.S. stock market, regardless of tweet content. It is relevant to note however, that the effect was stronger when Trump used confrontational words such as "tariff" or "trade war." Some of his announcements also influenced the U.S. dollar exchange rate (Vlastakis & Markellos (2012)) and certain market indices within minutes of the tweet being posted (Colonescu (2018) and Kinyua et al. (2021)).

Furthermore, scholars have shown that negative Trump tweets about specific companies tended to reduce demand for their stocks (Brans & Scholtens (2020) and Mendels (2019)), whereas some others have shown that they also impact market volatility indices such as the VIX (Fendel et al. (2019)) or the Volfele (Klaus & Koser (2021)). The effects of his tweets also extended beyond the U.S.. For example, Nishimura & Sun (2025) show a positive relationship between volatility in European stock markets and Twitter activity of Trump, and this effect tends to intensify as public interest for his tweet grows.

2 Data

2.1 Financial Data

For our financial data, we decided to try to find minute-by-minute prices for broad market indices. Since the actual indices do not update their prices that often, we had to take proxies under the form of ETFs that track them. Our 3 markets of analysis are: SPY to track the S&P500, VGK to track the FTSE Developed Europe All Cap Index, and finally ASHR to track the CSI 300 China. We accessed this data through a free stock API, Alpha Vantage. Our timeframe starts on the first of January 2014 and goes to the 7th of May 2025.

We had to transform this data to get our main variable of interest, Average Hourly Volatility (AHV). Note that this is *realised* market volatility. We did so using the following formula:

$$v_t = \frac{1}{N}\sum_{i=1}^{N}(\Delta p_{t,i})^2$$

Where Δp_t is the difference in price (open - close) and i represents every minute.

Ultimately, we compute the AHV for each open market hour since 2014. Note that the first hour is from 9:30 am to 10:00 am since the market opens on a half-hour but closes at 4:00 pm. Plotting this data, we observe that the last few months display unprecedented levels of volatility which have reached, and even surpassed, levels seen during the COVID-19 pandemic.

2.2 Political Data

We have two types of data for Trump's posts, Tweets & "Truths" (from Truth Social). The Tweets are sourced from Kaggle Shantanu (n.d.) and stop in January 2021, seen as Trump was then banned. Due to that, we have a gap in data going until February 2022, when he first posted on his own new platform. All Truth Social posts were pulled from trumpstruth.org, a webpage that aims to conserve all his posts. Note that we have had to use web-scrapping methods in order to download all these posts in a dataset.

A big problem we had in our analysis was what to do with social media posts which appeared outside market hours. We first decided to simply ignore them, but it turned out to remove a lot of observations. We finally decided to push all the social media information outside market hours to the next open hour. This comes as a critical assumption[1].

Since our financial data is hourly, we aggregate the social data by hour. We then construct multiple variables this dataset. These include a dummy for whether there was a post ($TweetDummy$), the number of posts in an hour ($TweetCount$), and counts for mentions of certain words ($Tariff$,$Trade$, & $China$). Furthermore, we applied some simple sentiment analysis algorithms on the data to see if there are certain sentiments in his tweets that move the markets. Details on all our data management procedures can be found in the GitHub repository.

[1] For instance, if Trump tweets on Good Friday (market holiday), then the market will only react to this new information on Monday at 9:30 am.

3 ARMA-X

3.1 Methodology

We first thought of a simple ARMA-X type specification, taking the AHV as our "y variable" and taking any of the social media variables as the exogenous regressors. The assumption here is that, while the market reacts to Trump posts, Trump's posts are chaotic, nonsensical, and random enough to be considered exogenous.

We of course first start by checking stationarity of our variables (using ADF tests), where we find p-values of 0.01 suggesting that the processes are not explosive. Then, we use a custom function in order to choose the number of lags based on the AIC criterion. This would often choose a very high number of lags, which could be explained by our data being hourly. As such we decided to put a limit of 3 lags, which sees minimal AIC loss and allows the simplifying of our models considerably.

3.2 Results

3.2.1 Full Timeframe

We run models with the following exogenous regressors: $TweetDummy$, $TweetCount$, and the mentions of words $Tariff$, $Trade$, and $China$. We first note in Table 1 that all the x-regressors are significant, apart from $Trade$. Notice also that all the coefficients (apart from $Tariff_{t-3}$) are positive, in line with our main hypothesis. The effect of $Tariff_{t-1}$ and $Tariff_{t-2}$ are especially large, given the average size of the volatility being about 0.023 over the whole sample. We in fact predict that an extra mention of tariffs one hour ago leads to a whopping extra 0.02 in volatility which means it would just about double the AHV if at the average. We can see the impulse response function (IRF) for this shock, in Figure 2. Notice that there is a large positive response in the first periods, and then a graduate decline over time. Something to note is that in our various analyses, when including MA terms, the decline shows up gradual while being much sharper when only including AR terms. We also ran all these models on the VGK and ASHR ETFs, though no significant results appear apart from a small but statistically significant effect of the tariff variable for VGK.

3.2.2 Split Samples

We then split our sample for the first and second term of the Trump presidency to explore whether there has been a shift in how markets respond from the first presidency. We only run models using $Tariff$, $Trade$ and $China$. As seen on Table 2, the first interesting result is in the coefficients of $Tariff$ being significant and very large in the second term, while being small and not statistically significant in the first. A similar story goes for the $China$ variable. This may lend some evidence to support the claim that investors are much more reactive to Trump's social media presence now than before. We've found similar IRFs as for the full timeframe. Finally, we can check the residuals of all these models to test them somewhat. We find that p-values are zero for the full timeframe and first term models, which suggests that there is significant auto-correlation, thus suggesting that these estimations are problematic. However, for the second term, the p-values are quite high (~ 0.8 for $Tariff$), lending support to our models on the split sample. These results suggest that perhaps ARMA-X models are not quite right in this context as it is not unreasonable to think that Trump does in fact react to market movements, which would break the exogeneity assumption that is critical for this type of model. With this information, we decide to run an SVAR model to account for possible endogeneity.

4 SVAR

4.1 Methodology

We develop an SVAR model in order to assess the impact of short-run shocks from Trump's posts on AHV, and to evaluate whether market volatility can, in turn, influence Trump's posting behaviour. In this framework, we systematically pair AHV with one explanatory variable at a time (our X-regressor). The SVAR approach offers the advantage of accounting for structural endogeneity. Our main assumption is that the volatility does not contemporaneously affect Trump's posting activity - neither quantitatively nor qualitatively, while Trump's posts do affect markets instantly. In essence, we impose a short-run restriction on the shock of volatility for all the social media variables.

Based on the information criteria, we found similar results across all specifications, with a recommended lag length of around 70. However, including more than 6 lags (corresponding to a full trading day) introduces strong seasonality.

Moreover, the higher the number of lags, the greater the persistence of a shock, up to unrealistic levels such as 150 days for the number of Tweets, which seems implausible. Therefore, we chose to fix the number of lags at a maximum of 6. Finally, given the presence of heteroscedasticity and serial correlation in the residuals, we use the Newey-West estimator to compute robust standard errors.

4.2 Results

4.2.1 Full Timeframe

As in the ARMA-X framework, we initially estimate a model for each of our five main variables across the full dataset. Table 3 shows all estimations using the SPY ETF, where we notice that the positive coefficients (of the social media variables) are large but not statistically significant. Oddly, the only significant coefficients are consistently negative.

For the $Tariff$, $Trade$ and $China$ variables, the first, second and sometimes fourth lags are positive and relatively large (especially in the case of $Tariff$), while the remaining ones are not. In contrast, for $TweetCount$ and $TweetDummy$, we observe fewer and smaller positive coefficients. At the same time, we find that the contemporaneous effects of the shocks are all positive and relatively strong. This leads to two types of scenarios : either the IRFs experience a positive shock and remain elevated $Tariff$, $Trade$ and $China$), or a highly positive shock occurs, but the cumulative effect turns negative after a few hours ($TweetDummy$ and $Count$). You can find the IRFs for $Tariff$ on Figures 3 and 4.

Finally, apart for $Tariff$, all Granger causality tests indicate that Trump's posts Granger-cause volatility. However, due to serial correlation in the residuals, these results should be interpreted with extreme caution. Overall, this model suggests that Trump's posts tend to have a positive instantaneous effect on volatility, but with very low persistence. When analyzing the VGK & ASHR ETFs, we observe similar patterns though with lower magnitude, except for the impact of $Tariff$ and $China$ on ASHR, where the cumulative effects show no positive impact. Additionally, the VGK ETF appears to react more strongly than ASHR to Trump's posts, especially those mentioning $Trade$ and $Tariff$.

Regarding the impact of AHV on Trump's posts, we find some evidence of a negative effect. For all variables, we observe one or two significantly negative coefficients per variables, typically on the first and fourth lag, alongside many insignificant ones. However, only $TweetCount$ and $China$ pass the Granger test in the SPY ETF. Surprisingly, a large number of Granger tests in the VGK and ASHR ETFs indicate strong Granger causality, which may point to a limitation of the test itself, as such results appear unrealistic.

4.2.2 Split Sample

Tables 4 and 5 show the models for the split terms, where we notice the results are similar and striking. While we observe relatively small shock effects and almost entirely negative coefficients during the first term, (which explain why the cumulative IRFs indicate a negative impact of posts), the shock effects in the second term are substantially larger, ranging from 5 times (for $TweetCount$ and $TweetDummy$) to as much as 25 times greater (for $Tariff$). the only exception is $Trade$ in the second term, which shows the only negative impact from a shock. Once again, we find positive lagged coefficients in the second term, mostly on the first, second and fourth lags. However, none of these coefficients are statistically significant, though the cumulative IRFs clearly show a high positive impact on everything except for $TweetDummy$ and $TweetCount$, whose coefficients and cumulative IRFs display similar patterns to those observed in the first term.

Moreover, the Granger tests generally failed in both terms, with the sole exception being $China$ in the second term. Regarding the ASHR ETF, we found results similar to those for SPY. Surprisingly, in the case of VGK, we observe a positive impact of Trump's posts on AHV during the first term. Nevertheless, the results still indicate a stronger impact of posts during the second term.

5 Conclusion

We started this project with the intention of understanding whether the impact of Trump's social media posts affect financial markets, and to see if there is perhaps a difference from his first presidential mandate. After various headaches with our data, we first ran ARMA-X models where we found significant and positive results albeit with strong auto-correlation in the errors, with only the second term analysis offering more convincing results. We then tried SVAR models for a possibly more accurate picture, albeit with little to no success. We once again found strong auto-correlation in the errors, which we fixed by using Newey-West standard errors. We found that the only significant coefficients are actually negative, suggesting Trump's social media presence would reduce volatility.

Alltogether, we would strongly suggest against trying to interpret these results given that the models seem to not fit particularly well. This may be due to seasonality in our data (a common trend seen in our daily AVH being high volatility in the first open hours, and a gradual slowdown for the rest of the day), or to our handling of non-market hours. Further work could look at exploring said issues in greater depth, further complicate the models by adding more variables and interactions between them, and/or additionally use more sophisticated models with very large lag counts.

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7 Appendix

7.1 ARMAX

7.1.1 SPY ARMA-X Models (Jan 2014 - May 2025)

Table 1: ARMA-X Models of Average Hourly Volatility

	Model 1	Model 2	Model 3	Model 4	Model 5
AR(1)	0.0300	0.0278	0.2200^{***}	2.1903^{***}	0.2209^{***}
	(0.0510)	(0.0510)	(0.0084)	(0.0096)	(0.0084)
AR(2)	0.7229^{***}	0.7210^{***}	0.9388^{***}	-1.4727^{***}	0.9382^{***}
	(0.0397)	(0.0399)	(0.0037)	(0.0173)	(0.0037)
AR(3)	0.2110^{***}	0.2148^{***}	-0.1837^{***}	0.2784^{***}	-0.1837^{***}
	(0.0287)	(0.0284)	(0.0079)	(0.0082)	(0.0079)
MA(1)	0.2751^{***}	0.2779^{***}	0.0870^{***}	-1.8955^{***}	0.0878^{***}
	(0.0496)	(0.0496)	(0.0042)	(0.0062)	(0.0042)
MA(2)	-0.6445^{***}	-0.6430^{***}	-0.8960^{***}	0.9165^{***}	-0.8950^{***}
	(0.0284)	(0.0285)	(0.0042)	(0.0063)	(0.0042)
MA(3)	-0.3527^{***}	-0.3563^{***}			
	(0.0256)	(0.0253)			
$TweetDummy_t$	0.0014^{***}				
	(0.0002)				
$TweetDummy_{t-1}$	0.0008^{***}				
	(0.0002)				
$TweetCount_t$		0.0004^{***}			
		(0.0001)			
$TweetCount_{t-1}$		0.0002^{**}			
		(0.0001)			
$Tariff_t$			0.0035^{*}		
			(0.0014)		
$Tariff_{t-1}$			0.0191^{***}		
			(0.0015)		
$Tariff_{t-2}$			0.0103^{***}		
			(0.0015)		
$Tariff_{t-3}$			-0.0045^{**}		
			(0.0014)		
$Trade_t$				0.0032	
				(0.0018)	
$Trade_{t-1}$				0.0016	
				(0.0018)	
$China_t$					0.0026^{*}
					(0.0012)
AIC	−45761.2161	−45737.6695	−46020.9547	−45816.1540	−45840.5349
AICc	−45761.2051	−45737.6585	−46020.9415	−45816.1449	−45840.5277
BIC	−45682.1963	−45658.6497	−45934.0340	−45745.0361	−45777.3186
Log Likelihood	22890.6081	22878.8348	23021.4774	22917.0770	22928.2675
Num. obs.	19970	19970	19968	19970	19971

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

7.1.2 SPY ARMA-X IRF

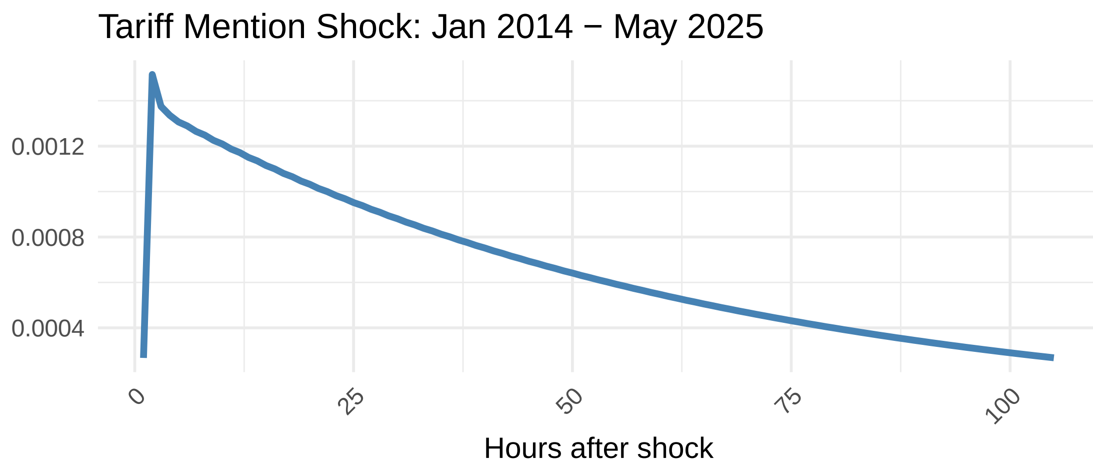

Figure 2: ARMA-X IRF

7.1.3 SPY ARMA-X Split Models

Table 2: Split-Term ARMA-X Models of Average Hourly Volatility

	First Term (1)	First Term (2)	First Term (3)	Second Term (1)	Second Term (2)	Second Term (3)
AR(1)	0.2953***	0.2943***	0.2927***	0.9686***	0.9683***	0.9693***
	(0.0225)	(0.0224)	(0.0224)	(0.0163)	(0.0163)	(0.0161)
AR(2)	0.1434***	0.1439***	0.1438***			
	(0.0220)	(0.0220)	(0.0219)			
AR(3)	0.5456***	0.5462***	0.5480***			
	(0.0223)	(0.0222)	(0.0222)			
MA(1)	0.1854***	0.1863***	0.1866***	−0.6965***	−0.6905***	−0.7207***
	(0.0180)	(0.0179)	(0.0179)	(0.0469)	(0.0469)	(0.0467)
MA(2)	−0.1707***	−0.1706***	−0.1695***	−0.1732***	−0.1755***	−0.1609***
	(0.0169)	(0.0169)	(0.0168)	(0.0437)	(0.0438)	(0.0434)
MA(3)	−0.6557***	−0.6564***	−0.6575***			
	(0.0162)	(0.0161)	(0.0161)			
$Tariff_t$	0.0011			0.0048		
	(0.0010)			(0.0099)		
$Tariff_{t-1}$				0.0278**		
				(0.0102)		
$Tariff_{t-2}$				0.0168		
				(0.0099)		
$Trade_t$		0.0023**			−0.0074	
		(0.0009)			(0.0297)	
$China_t$			0.0018**			0.0173
			(0.0006)			(0.0319)
$China_{t-1}$						0.1515***
						(0.0324)
$China_{t-2}$						0.1309***
						(0.0319)
AIC	−28604.6559	−28610.2269	−28613.1693	633.4836	638.2093	610.2140
AICc	−28604.6303	−28610.2013	−28613.1437	633.7676	638.3737	610.4980
BIC	−28542.9191	−28548.4901	−28551.4325	667.4525	663.7092	644.1829
Log Likelihood	14311.3279	14314.1134	14315.5847	−308.7418	−313.1047	−297.1070
Num. obs.	7042	7042	7042	516	518	516

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

7.2 SVAR

7.2.1 SPY SVAR Models (Jan 2014 - May 2025)

Table 3: SVAR Models of Average Hourly Volatility

	TweetDummy	TweetCount	Tariff	Trade	China
AHV_{t-1}	0.3445^{***}	0.3450^{***}	0.3421^{***}	0.3461^{***}	0.3445^{***}
	(0.1038)	(0.1045)	(0.0987)	(0.1019)	(0.0980)
AHV_{t-2}	0.0237	0.0236	0.0275	0.0229	0.0241
	(0.0427)	(0.0438)	(0.0399)	(0.0415)	(0.0436)
AHV_{t-3}	0.0829^{***}	0.0825^{***}	0.0754^{***}	0.0811^{***}	0.0816^{***}
	(0.0075)	(0.0081)	(0.0117)	(0.0083)	(0.0092)
AHV_{t-4}	0.0969	0.0967	0.0888	0.0958	0.0949
	(0.0593)	(0.0608)	(0.0639)	(0.0571)	(0.0588)
AHV_{t-5}	0.0229^{***}	0.0226^{**}	0.0260^{***}	0.0235^{**}	0.0230^{**}
	(0.0069)	(0.0070)	(0.0068)	(0.0072)	(0.0077)
AHV_{t-6}	0.1640^{***}	0.1644^{***}	0.1675^{***}	0.1653^{***}	0.1667^{**}
	(0.0474)	(0.0498)	(0.0499)	(0.0493)	(0.0542)
X_{t-1}	0.0001	0.0000	0.0197	0.0034	0.0067
	(0.0002)	(0.0000)	(0.0190)	(0.0037)	(0.0067)
X_{t-2}	-0.0005^{***}	-0.0001^{***}	0.0053	0.0056	0.0028
	(0.0001)	(0.0000)	(0.0041)	(0.0048)	(0.0041)
X_{t-3}	-0.0008^{***}	-0.0002^{***}	-0.0078	-0.0039^{*}	-0.0047^{*}
	(0.0001)	(0.0000)	(0.0052)	(0.0017)	(0.0021)
X_{t-4}	-0.0005^{***}	-0.0001^{***}	0.0023	0.0007	-0.0024^{*}
	(0.0001)	(0.0000)	(0.0025)	(0.0035)	(0.0011)
X_{t-5}	-0.0006^{***}	-0.0001^{**}	-0.0011	-0.0024	-0.0006
	(0.0001)	(0.0000)	(0.0026)	(0.0019)	(0.0010)
X_{t-6}	-0.0001	0.0000	-0.0028	-0.0015	0.0006
	(0.0001)	(0.0000)	(0.0024)	(0.0012)	(0.0010)
Constant	0.0087^{***}	0.0076^{***}	0.0058^{***}	0.0059^{***}	0.0059^{***}
	(0.0016)	(0.0016)	(0.0014)	(0.0015)	(0.0016)
Shock (IRF)	0.0042	0.0031	0.0012	0.0002	0.0019
R^2	0.3257	0.3253	0.3319	0.3251	0.3263
Adj. R^2	0.3253	0.3249	0.3315	0.3247	0.3259
Num. obs.	19965	19965	19965	19965	19965

Each SVAR regression has only two variables: AHV and X. The column names represent the X variable for the selected model.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

7.2.2 SPY SVAR IRFs

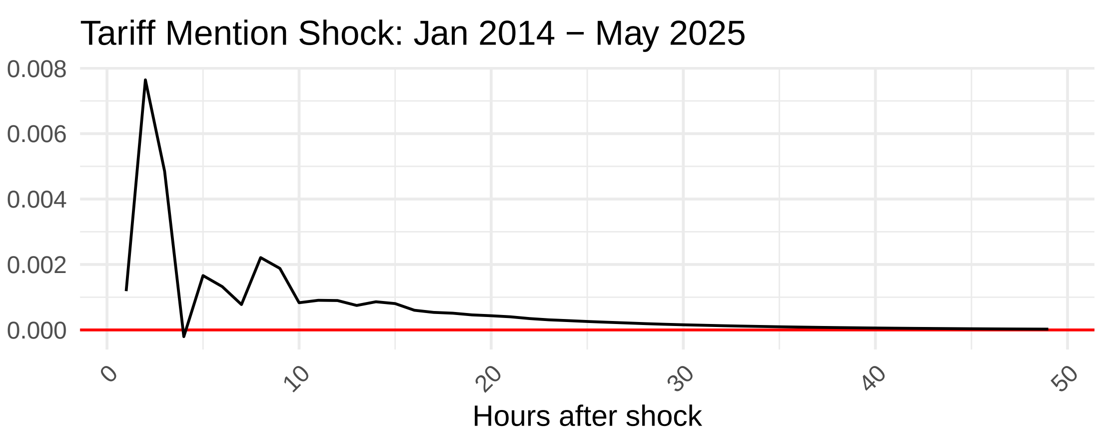

Figure 3: SVAR IRF 1

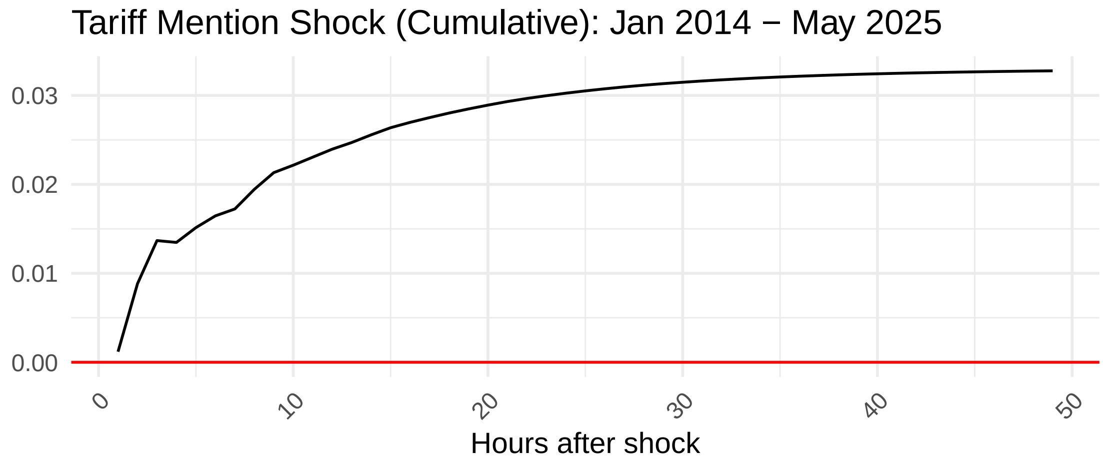

Figure 4: SVAR IRF 2

7.2.3 SPY SVAR First-Term Models

Table 4: First-Term SVAR Models of Average Hourly Volatility

	TweetDummy	TweetCount	Tariff	Trade	China
AHV_{t-1}	0.5419^{***}	0.5424^{***}	0.5436^{***}	0.5440^{***}	0.5435^{***}
	(0.0741)	(0.0743)	(0.0750)	(0.0752)	(0.0750)
AHV_{t-2}	-0.1139^{**}	-0.1139^{**}	-0.1151^{**}	-0.1156^{**}	-0.1150^{**}
	(0.0388)	(0.0393)	(0.0396)	(0.0391)	(0.0396)
AHV_{t-3}	0.0581^{*}	0.0576^{*}	0.0536^{*}	0.0536^{*}	0.0544^{*}
	(0.0275)	(0.0272)	(0.0271)	(0.0269)	(0.0275)
AHV_{t-4}	0.1884	0.1874	0.1842	0.1841	0.1846
	(0.1326)	(0.1314)	(0.1306)	(0.1336)	(0.1310)
AHV_{t-5}	-0.0888	-0.0897	-0.0915	-0.0917	-0.0918
	(0.0915)	(0.0907)	(0.0910)	(0.0933)	(0.0911)
AHV_{t-6}	0.3367^{***}	0.3377^{***}	0.3434^{***}	0.3435^{***}	0.3432^{***}
	(0.0490)	(0.0488)	(0.0484)	(0.0485)	(0.0489)
X_{t-1}	-0.0005^{***}	-0.0002^{**}	-0.0005	-0.0018^{*}	-0.0004
	(0.0001)	(0.0001)	(0.0004)	(0.0007)	(0.0004)
X_{t-2}	-0.0002^{**}	-0.0001^{*}	-0.0003	0.0002	-0.0000
	(0.0001)	(0.0000)	(0.0003)	(0.0005)	(0.0002)
X_{t-3}	-0.0007^{***}	-0.0003^{***}	-0.0010^{***}	-0.0009^{**}	-0.0014^{***}
	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0004)
X_{t-4}	-0.0006^{***}	-0.0002^{**}	-0.0003	-0.0006	-0.0002
	(0.0002)	(0.0001)	(0.0004)	(0.0004)	(0.0005)
X_{t-5}	-0.0004^{***}	-0.0001^{**}	-0.0005	-0.0006	-0.0001
	(0.0001)	(0.0000)	(0.0003)	(0.0004)	(0.0004)
X_{t-6}	0.0001	0.0001^{*}	0.0002	-0.0001	0.0003
	(0.0001)	(0.0000)	(0.0003)	(0.0004)	(0.0004)
Constant	0.0040^{***}	0.0031^{***}	0.0015^{***}	0.0017^{***}	0.0016^{***}
	(0.0007)	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Shock (IRF)	0.0029	0.0022	0.0005	0.0007	0.0009
R^2	0.6879	0.6872	0.6853	0.6855	0.6855
Adj. R^2	0.6873	0.6867	0.6848	0.6849	0.6850
Num. obs.	7036	7036	7036	7036	7036

Each SVAR regression has only two variables: AHV and X. The column names represent the X variable for the selected model.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

7.2.4 SPY SVAR Second-Term Models

Table 5: Second-Term SVAR Models of Average Hourly Volatility

	TweetDummy	TweetCount	Tariff	Trade	China
AHV_{t-1}	0.2994^{**}	0.2993^{*}	0.2948^{**}	0.3012^{**}	0.2744^{***}
	(0.1124)	(0.1160)	(0.1103)	(0.1112)	(0.0785)
AHV_{t-2}	0.0154	0.0136	0.0207	0.0118	0.0317
	(0.0437)	(0.0452)	(0.0387)	(0.0436)	(0.0283)
AHV_{t-3}	0.0762^{***}	0.0769^{***}	0.0687^{***}	0.0723^{***}	0.0527
	(0.0085)	(0.0088)	(0.0163)	(0.0140)	(0.0345)
AHV_{t-4}	0.0842	0.0851	0.0744	0.0805	0.0356
	(0.0679)	(0.0710)	(0.0798)	(0.0667)	(0.1009)
AHV_{t-5}	0.0134^{**}	0.0104	0.0153^{**}	0.0176^{*}	0.0055
	(0.0051)	(0.0060)	(0.0054)	(0.0083)	(0.0322)
AHV_{t-6}	0.1266^{*}	0.1263^{*}	0.1321^{**}	0.1243^{*}	0.1509^{**}
	(0.0500)	(0.0509)	(0.0492)	(0.0514)	(0.0511)
X_{t-1}	0.0066	0.0009	0.0270	0.0205	0.1546
	(0.0101)	(0.0013)	(0.0286)	(0.0299)	(0.1381)
X_{t-2}	-0.0032^{**}	-0.0007	0.0086	0.0472	0.0993
	(0.0010)	(0.0005)	(0.0072)	(0.0413)	(0.0950)
X_{t-3}	-0.0055^{**}	-0.0016^{*}	-0.0103	-0.0266	-0.0477
	(0.0017)	(0.0007)	(0.0076)	(0.0213)	(0.0300)
X_{t-4}	0.0025	0.0001	0.0020	0.0199	-0.0207
	(0.0050)	(0.0009)	(0.0030)	(0.0316)	(0.0124)
X_{t-5}	-0.0085^{*}	-0.0017	-0.0026	-0.0130	-0.0045
	(0.0040)	(0.0011)	(0.0043)	(0.0150)	(0.0183)
X_{t-6}	-0.0036	-0.0006	-0.0043	-0.0111	0.0080
	(0.0032)	(0.0008)	(0.0039)	(0.0103)	(0.0223)
Constant	0.0725^{**}	0.0684^{**}	0.0493^{**}	0.0521^{***}	0.0440^{*}
	(0.0242)	(0.0213)	(0.0153)	(0.0143)	(0.0175)
Shock (IRF)	0.0147	0.0133	0.0108	-0.0057	0.0139
R^2	0.2441	0.2408	0.2513	0.2444	0.2852
Adj. R^2	0.2244	0.2210	0.2318	0.2247	0.2665
Num. obs.	512	512	512	512	512

Each SVAR regression has only two variables: AHV and X. The column names represent the X variable for the selected model.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.