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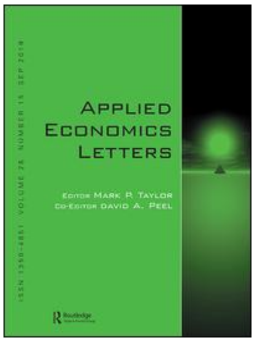

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ARTICLE

Disapproval rating, VIX index, COVID-19 cases and Trump's tweeting against China

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ABSTRACT

The primary goal of this paper is to provide empirical evidence for how non-trade factors attribute to the China-US trade war. Trump's tweets provide us with a unique perspective. After analysing 31,166 Trump's tweets, we have the following findings: (1) It's non-trade factors rather than trade-related factors that can significantly predict whether Trump posts negative tweets involving China's economic and trade issues. For every 1% increase in Trump's disapproval rating and VIX index, the likelihood of Trump posting negative tweets involving China's economic and trade issues increases by 0.61% and 0.16% respectively. (2) Tweeting against China sometimes becomes a tool to divert domestic criticism. After the COVID-19 outbreak, the higher growth rate of cumulative COVID-19 confirmed cases, the higher likelihood of Trump tweeting against China. (3) Tweeting against China can win public support and attention. Holding everything else constant, the number of likes and retweets of negative tweets about China are 10.2% and 14.6% more than those of positive tweets about China.

KEYWORDS

Trade war; Twitter; Trump; text analysis; COVID-19

I. Introduction

There is extensive literature on political economy which considers how non-trade factors attribute to the trade war. Mayer (1984) demonstrates how voters' preferences affect the trade policy formation. Grossman and Helpman (1995) note that interest groups lobbying may lead to trade war. Recently, some insightful studies have shown that the root cause of China-US trade war is not merely trade issues. Chen et al. (2020) posit that the trade war is not about trade but about technological dominance. Other studies note that presidential election, domestic political polarization, and dissatisfaction with the income inequality act as important triggers for China-US trade war (CCWE, 2018; Chong and Li, 2019; Qiu et al., 2019; Stangarone, 2019). Our paper contributes to the literature by providing empirical evidence on the importance of non-trade factors.

Trump's tweets provide us a unique perspective to study the causes of China-US trade war (Figure 1). On the one hand, Trump is an addicted Twitter user and many trade policies are first announced through his Twitter account. The evolution of the number, theme, and sentiment of his tweets about China can reflect the trend of China-US trade war. On the other hand, Trump's Twitter account has 87 million followers. They can read the updates and freely decide whether to like, reply, or retweet each tweet. This enables us to study public feedback on different policies. Burggraf et al. (2020) analysed Trump's tweets in a pioneering piece of research, finding that tweets from Trump have significant negative effects on stock prices and positive effects on VIX. Inspired by this paper, we use Trump's tweets to investigate how non-trade factors attribute to the China-US trade war.

II. Data

This study uses 31,166 tweets posted by @realDonaldTrump after Trump announced his candidacy on 16 June 2015. The primary data source comes from the Trump Twitter Archive (http://www.trumptwitterarchive.com).

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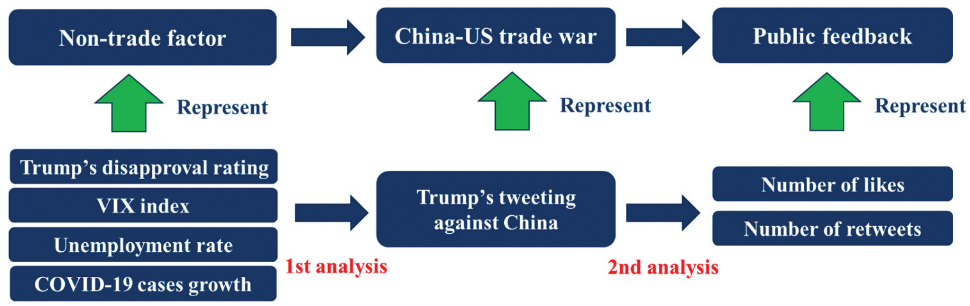

Figure 1. The logic of this study.

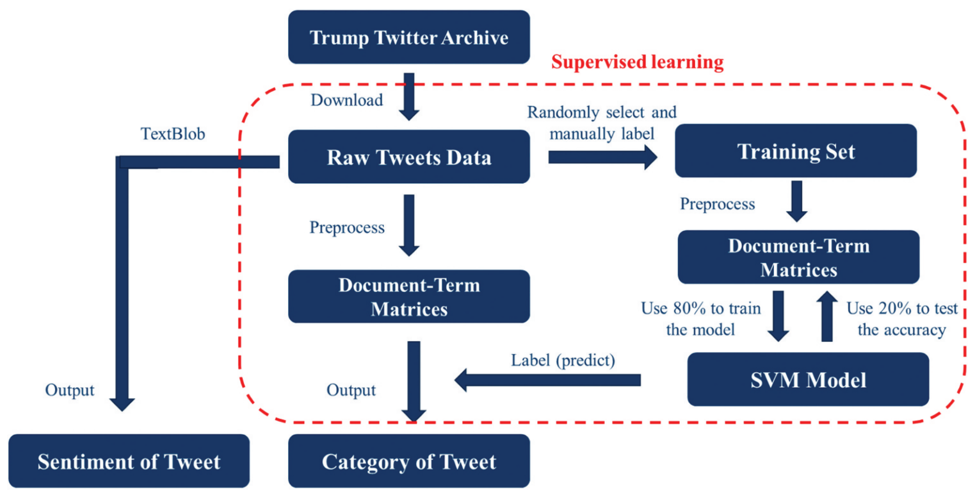

Figure 2. Flowchart of natural language processing.

We apply supervised learning (SL) methods to categorize the tweets (Figure 2). First, we randomly select 5,700 tweets from all samples to create a training set. We manually label each tweet with two tags: *china* and *theme*. *china* (dummy variable) denotes whether the tweet is related to China. *theme* (factor variable) denotes the theme of the tweet.[1] Tweets are preprocessed before being passed to the classifier (Abdelwahab et al., 2015; Zhao and Gui, 2017). Then, we use the SVM model for supervised learning. 80% of the training set is used to train the model, and the rest is used to test the accuracy of the trained model. For *china*, the accuracy rate is close to 100%; for *theme*, the average accuracy rate also reaches 74%, which shows the SVM model produces acceptable classification accuracy. Finally, we use the trained model to label all 31,166 tweets. To further improve the classification accuracy, we use keywords to filter the labelled results. Additionally, we perform sentiment analysis on each tweet using TextBlob, a text assessment package in Python.

We then summarize and visualize the labelled data. We find that tweets about China account for about 4% of the total tweets in recent years (Figure 3). Since 2016, the number and proportion of negative tweets about China have been steadily increasing. We also draw word cloud for Trump's China-related tweets (Figure 4). It clearly shows that trade issues have always been Trump's major concern.

III. Estimation

To empirically test the motivations and feedbacks of Trump's tweeting against China, we run two separate analyses. In the first analysis, we apply a logistic regression model to analyse Trump's likelihood of posting negative tweets involving China's economic and trade issues.

[1]We divide all tweets into six topics: domestic politics, crisis response, news media, economics and trade, security and diplomacy, and others.

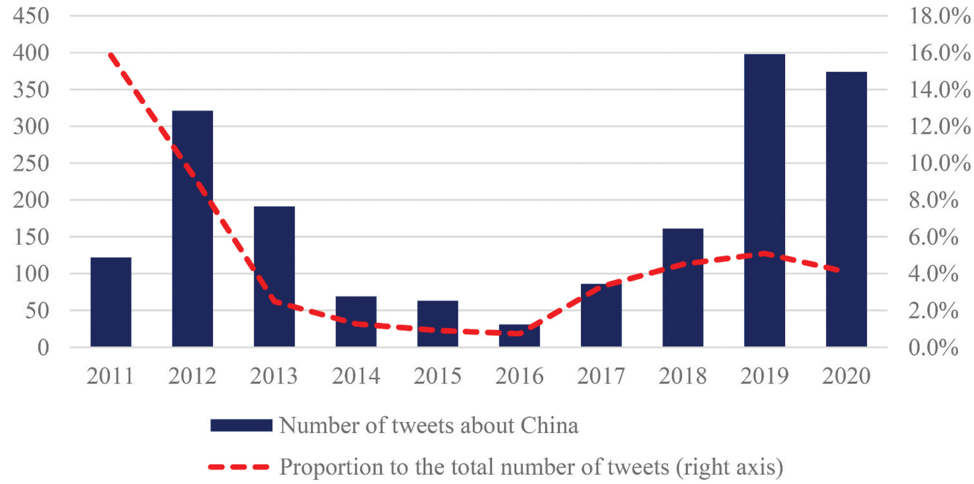

Figure 3. Descriptive statistics of Trump's China-related tweets.

Figure 4. Keywords in Trump's China-related tweets.

$$P(ChinaNegTrade_t = 1) = F[\alpha + \beta_1 log(disapproval_{t-1}) + \beta_2 log(vix_{t-1}) + \beta_3 unemployment_{t-1} + \beta_4 log(chinadeficit_{t-1}) + \beta_5 log(deficit_{t-1}) + \varepsilon_t] \quad (1)$$

Where t is the unit of analysis and indicates the number of days after Trump took office. The dependent variable $ChinaNegTrade_t$ denotes whether Trump posts negative tweets involving China's economic and trade issues during the period from t to $t+2$. The independent variables include three non-trade factors $disapproval_{t-1}$, vix_{t-1}, and $unemployment_{t-1}$, which are corresponding RCP President Trump Job Disapproval Rate, CBOE volatility index, and US unemployment rate. Our control variables include two trade-related factors $chinadeficit_{t-1}$ and $deficit_{t-1}$, which denotes US-China merchandise trade deficit and US merchandise trade deficit. For all independent variables and control variables, we use the moving average of the past seven days in order to avoid the effect of Trump's tweet affecting such variables as discovered by Burggraf et al. (2020).

In the second analysis, we apply a linear regression model to analyse the public feedback after Trump posts negative tweets about China.

Table 1. Summary statistics.

	N	Mean	Std.Dev	Min	Max
ChinaNegTrade	1935	0.120	0.325	0	1
log(disapproval)	1343	3.977	0.0350	3.789	4.059
log(vix)	1934	2.773	0.361	2.234	4.312
unemployment	1910	4.934	2.135	3.561	14.83
log(chinadeficit)	1910	10.30	0.204	9.379	10.67
log(deficit)	1910	11.12	0.0860	10.95	11.33
log(like)	22000	10.35	1.593	0	13.69
log(retweet)	22000	9.066	1.387	0	12.82
ChinaNeg	24000	0.0150	0.121	0	1
ChinaPos	24000	0.0240	0.153	0	1
OtherNeg	24000	0.450	0.498	0	1
OtherPos	24000	0.511	0.500	0	1
media	24000	0.333	0.471	0	1
log(length)	23000	2.224	0.732	0	3.497

$$log(like_i) = \alpha + \beta_1 ChinaPos_i + \beta_2 OtherNeg_i + \beta_3 OtherPos_i + \beta_4 media_i + \beta_5 log(length_i) + \sum_k \gamma_k theme_{ik} + \sum_g \theta_g ym_{ig} + \sum_j \mu_j week_{ij} + \varepsilon_i \tag{2}$$

Where i is the unit of analysis and indicates the series number of the tweet. The dependent variable $log(like_i)$ denotes the log number of likes for tweet i. We divide the tweets into four categories: negative tweets about China, other negative tweets, positive tweets about China, and other positive tweets. Our independent variables include $ChinaPos_i$, $OtherNeg_i$, and $OtherPos_i$, dummy variables that capture changes in the number of likes relative to the omitted group (negative tweets about China). Our control variables include ym_{ig} dummy variables that capture changes in the monthly average of the number of likes, a binary variable $media_i$ that is 1 for tweets with videos or pictures and 0 otherwise, $theme_{ik}$ factor variable that denotes the theme of the tweet, $length_i$ that equals the total number of words in the tweet, and $week_{ij}$ that controls the day-of-week fixed effect. Table 1 displays summary statistics.

IV. Results and discussion

Table 2 presents the first regression results from the simple OLS model (columns (1)-(2)), Logit model (columns (3)-(4), and Probit model (columns (5)-(6). Different models produce similar results. Counter-intuitively, the trade-related factors have no significant impact. While two non-trade factors, Trump's disapproval rating and VIX index significantly predict whether Trump posts negative tweets involving China's economic and trade issues. We assess the marginal effects at the mean. Coefficient estimates in column (5) suggest that for every 1% increase in Trump's disapproval rating and VIX index, the likelihood of Trump posting negative tweets involving China's economic and trade issues increases by 0.61% and 0.16% respectively.

To further test why Trump tweets against China, we change the dependent variable in the first regression from $ChinaNegTrade_t$ to $ChinaNeg_t$, which denotes whether Trump posts negative tweets about China. Table 3 presents the new regression results. Columns (1)-(3) show the VIX index and unemployment rate have significant

Table 2. The likelihood of Trump posting negative tweets involving China's economic and trade issues.

Dependent variable: $ChinaNegTrade_t$	OLS	OLS	Logit	Logit	mfx	Probit	Probit
	(1).	(2)	(3)	(4)	(5)	(6)	(7)
$log(disapproval_{t-1})$	0.684**	0.520*	6.862***	5.408**	0.613**	3.783***	2.938**
	(0.280)	(0.292)	(2.612)	(2.715)	(0.305)	(1.444)	(1.497)
$log(vix_{t-1})$	0.148***	0.171***	1.140***	1.422***	0.161***	0.655***	0.790***
	(0.030)	(0.038)	(0.230)	(0.312)	(0.0343)	(0.133)	(0.174)
$unemployment_{t-1}$	0.013***	0.012**	0.059*	0.044	0.00501	0.032*	0.025
	(0.005)	(0.005)	(0.031)	(0.031)	(0.00358)	(0.018)	(0.018)
$log(chinadeficit_{t-1})$		0.091		0.852	0.0966		0.464
		(0.061)		(0.523)	(0.0589)		(0.291)
$log(deficit_{t-1})$		0.014		0.324	0.0367		0.204
		(0.186)		(1.560)	(0.177)		(0.875)
Constant	−3.043***	−3.552*	−32.610***	−39.940**		−18.117***	−22.157**
	(1.130)	(1.932)	(10.602)	(16.858)		(5.860)	(9.465)
Observations	1319	1319	1319	1319	1319	1319	1319
$R^2/PseudoR^2$	0.054	0.057	0.0573	0.0621		0.0575	0.0624

This table reports the estimation results for Equation (1) based on the daily data after the beginning of the Trump presidency on 20 January 2017. The dependent variable $ChinaNegTrade_t$ denotes whether Trump posts negative tweets involving China's economic and trade issues during the period from t to $t+2$. The independent variables include three non-trade factors $disapproval_{t-1}$, vix_{t-1}, and $unemployment_{t-1}$, which denotes Trump's disapproval rating, VIX index and unemployment rate. Our control variables include two trade-related factors $chinadeficit_{t-1}$ and $deficit_{t-1}$, which denotes US-China merchandise trade deficit and US merchandise trade deficit. The standard errors are reported in parentheses. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3. The likelihood of Trump posting negative tweets about China.

	Full Sample			After the COVID-19 outbreak		
Dependent variable: $ChinaNeg_t$	OLS	Logit	Probit	OLS	Logit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
$log(disapprova_{t-1})$	0.205	0.621	0.483	0.024	0.496	0.224
	(0.384)	(1.958)	(1.183)	(1.421)	(6.486)	(3.959)
$log(vix_{t-1})$	0.202***	0.903***	0.558***	−0.293	−1.280	−0.767
	(0.050)	(0.240)	(0.146)	(0.180)	(0.834)	(0.501)
$unemployment_{t-1}$	0.024***	0.101***	0.062***	0.056***	0.248***	0.150***
	(0.006)	(0.030)	(0.018)	(0.020)	(0.094)	(0.056)
$covid19growth_{t-1}$				1.147***	5.161**	3.094**
				(0.435)	(2.005)	(1.206)
$log(chinadeficit_{t-1})$	−0.164**	−0.756**	−0.469**	−0.413	−1.861	−1.105
	(0.081)	(0.385)	(0.234)	(0.434)	(2.030)	(1.229)
$log(deficit_{t-1})$	0.807***	3.824***	2.362***	1.410*	6.221*	3.724*
	(0.245)	(1.201)	(0.724)	(0.832)	(3.644)	(2.231)
Constant	−8.442***	−40.933***	−25.661***	−10.759	−50.909	−30.276
	(2.543)	(12.665)	(7.641)	(6.941)	(31.384)	(19.015)
Observations	1319	1319	1319	228	228	228
$R^2/PseudoR^2$	0.117	0.0891	0.0896	0.110	0.0835	0.0830

This table reports the estimation results for Equation (1) based on the daily data after the beginning of the Trump presidency on 20 January 2017. The dependent variable $ChinaNeg_t$ denotes whether Trump posts negative tweets about China during the period from t to $t+2$. The independent variables include four non-trade factors $disapproval_{t-1}$, vix_{t-1}, $unemployment_{t-1}$, and $covid19growth_{t-1}$ which denotes Trump's disapproval rating, VIX index, unemployment rate and growth rate of cumulative COVID-19 confirmed cases. Our control variables include two trade-related factors $chinadeficit_{t-1}$ and $deficit_{t-1}$, which denotes US-China merchandise trade deficit and US merchandise trade deficit. The standard errors are reported in parentheses. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

positive effects on the likelihood of Trump posting negative tweets about China. We also find that the coefficients of US trade deficit are significantly positive, while the estimators of US-China trade deficit are significantly negative. This indicates that when the overall trade deficit of the US is expanding, Trump is more likely to tweet against China, ignoring the fact that the trade deficit between China and the US is actually declining. We also run the regression using samples after the COVID-19 outbreak, columns present the results. Interestingly, the coefficients of $covid19growth_{t-1}$ are significantly positive, which shows the higher growth rate of cumulative COVID-19 confirmed cases, the more negative tweets about China.

Table 4 presents the second regression results. Columns (1)-(3) represent the results of the baseline regression model, which analyzes the number of likes a tweet receives. The coefficients of $ChinaPos_i$, $OtherNeg_i$, and $OtherPos_i$ are all negative, which shows that negative tweets about China win public support. Coefficient estimates in column (3) suggest, holding everything else constant, the number of likes on negative tweets about China is 10.2% more than that of positive tweets about China. Furthermore, we change the dependent variable in the second regression from $log(like_i)$ to $log(retweet_i)$, which denotes the log number of retweets for tweet i. Columns (4)-(6) represent the results. We find that the previous conclusions are still robust, that is, negative tweets about China can win public attention. Our results also show that tweets with videos or pictures receive fewer likes and retweets. The more words in the tweet, the fewer likes and the more retweets.

V. Conclusions

This paper analyses 31,166 Trump's tweets, studies the motivations and feedbacks of Trump's tweeting against China, and provides empirical evidence for how non-trade factors attribute to the China-US trade war. Our empirical results support the following conclusions. (1) It is non-trade factors rather than trade-related factors that can significantly predict whether Trump posts negative tweets involving China's economic and trade issues. For every 1% increase in Trump's disapproval rating and VIX index, the likelihood of Trump posting negative tweets involving China's economic and trade issues increases by 0.61% and 0.16% respectively. (2) Tweeting against China sometimes becomes a tool to divert domestic criticism. After the COVID-19 outbreak, the higher growth rate of cumulative COVID-19 confirmed cases, the higher likelihood of Trump tweeting against China. (3) Tweeting against China can

Table 4. The number of likes and retweets for different tweets.

Variables	log(like)	log(like)	log(like)	log(retweet)	log(retweet)	log(retweet)
	(1)	(2)	(3)	(4)	(5)	(6)
ChinaPos	−0.103**	−0.103**	−0.102**	−0.146***	−0.147***	−0.146***
	(−0.048)	(−0.047)	(−0.047)	(−0.048)	(−0.048)	(−0.048)
OtherNeg	−0.138***	−0.053	−0.054	−0.121***	−0.059	−0.059
	(−0.039)	(−0.038)	(−0.038)	(−0.039)	(−0.039)	(−0.039)
OtherPos	−0.125***	−0.082**	−0.082**	−0.184***	−0.154***	−0.154***
	(−0.039)	(−0.038)	(−0.038)	(−0.039)	(−0.039)	(−0.039)
media		−0.348***	−0.345***		−0.179***	−0.176**
		(−0.011)	(−0.011)		(−0.012)	(−0.012)
length		−0.057***	−0.057***		0.016**	0.016**
		(−0.007)	(−0.007)		(−0.007)	(−0.007)
Constant	5.958***	6.082***	6.091***	5.109***	5.072***	5.082***
	(−0.057)	(−0.058)	(−0.059)	(−0.056)	(−0.059))	(−0.06)
Day-of-Week dummies	No	No	Yes	No	No	Yes
Theme dummies	No	Yes	Yes	No	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22060	20988	20988	22063	20991	20991
R^2	0.815	0.83	0.831	0.758	0.769	0.769

This table reports the estimation results for Equation (2) based on the data of 22,060 original tweets posted after Trump announced his presidential campaign on 16 June 2016. The dependent variables $log(like_i)$ and $log(retweet_i)$ denote the log number of likes and retweets for tweet *i*. $ChinaPos_i$, $OtherNeg_i$, and $OtherPos_i$ are dummy variables that capture changes in the number of likes or retweets relative to the omitted group (negative tweets about China). $media_i$ denotes whether the tweet contains videos or pictures, $length_i$ is equal to the total number of words in the tweet. The Standard errors are reported in parentheses. * significant at 10% level; ** significant at 5% level; *** significant at 1% level win public support and attention. Holding everything else constant, the number of likes and retweets of negative tweets about China are 10.2% and 14.6% more than those of positive tweets about China.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abdelwahab, O., M. Bahgat, C. J. Lowrance, and A. Elmaghraby 2015, December. "Effect of Training Set Size on SVM and Naive Bayes for Twitter Sentiment Analysis." In *2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, 46–51. IEEE.

Burggraf, T., R. Fendel, and T. L. D. Huynh. 2020. "Political News and Stock Prices: Evidence from Trump's Trade War." *Applied Economics Letters* 27 (18): 1485–1488. doi:10.1080/13504851.2019.1690626.

Centre for China in the World Economy. 2018. "Strategic Report on Sino-US Economic and Trade Relations." Accessed 7 November 2020. http://www.ccwe.tsinghua.edu.cn/info/jqhd/2247

Chen, A. W., J. Chen, and V. R. Dondeti. 2020. "The US-China Trade War: Dominance of Trade or Technology?" *Applied Economics Letters* 27 (11): 904–909. doi:10.1080/13504851.2019.1646860.

Chong, T. T. L., and X. Li. 2019. "Understanding the China–US Trade War: Causes, Economic Impact, and the Worst-case Scenario." *Economic and Political Studies* 7 (2): 185–202. doi:10.1080/20954816.2019.1595328.

Grossman, G. M., and E. Helpman. 1995. "Trade Wars and Trade Talks." *Journal of Political Economy* 103 (4): 675–708. doi:10.1086/261999.

Mayer, W. 1984. "Endogenous Tariff Formation." *The American Economic Review* 74 (5): 970–985.

Qiu, L. D., C. Zhan, and X. Wei. 2019. "An Analysis of the China–US Trade War through the Lens of the Trade Literature." *Economic and Political Studies* 7 (2): 148–168. doi:10.1080/20954816.2019.1595329.

Stangarone, T. 2019. "Domestic Sources of the US Trade War with China." *East Asian Policy* 11 (4): 5–18. doi:10.1142/S1793930519000321.

Zhao, J., and X. Gui. 2017. "Comparison Research on Text Pre-processing Methods on Twitter Sentiment Analysis." *IEEE Access* 5: 2870–2879. doi:10.1109/ACCESS.2017.2672677.