Title:

Increase in number of suicide preventive tweets during suicide prevention periods in Japan: Results of a time-series analysis

Toshiharu Mitsuhashi [*1]
*1 Center for Innovative Clinical Medicine, Okayama University Hospital.

Address correspondence and reprint requests to:
Toshiharu Mitsuhashi
Center for Innovative Clinical Medicine, Okayama University Hospital.
2-5-1 Shikata-cho, Kita-ku, Okayama 700-8558, Japan.
Phone +81(JPN)-86-223-7151 (ext. 7176), FAX +81(JPN)-86-235-7178.
E-mail: mitsuh-t@cc.okayama-u.ac.jp

Running title
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Abstract

Objective: The number of suicides in Japan is about 30 000 people a year. In Japan, Suicide Prevention Weeks (September 10 to September 16) and Suicide Support Measure Reinforcement Months (March) have been established, and efforts to appropriately educate the public are implemented. The impact of posting on social media is growing in today's world. However, efforts taking into consideration the spread of suicide-related information via social media during these periods have been inadequate. In this study, we assess whether the number of postings ("tweets") on Twitter changes during these periods.

Subjects and Methods: I targeted tweets posted between January 1, 2011 and December 31, 2014. I defined the number of suicide-prevention-related tweets as "number of preventive tweets" and the number of other suicide-related tweets as "number of related tweets". The number of tweets posted each day was calculated and analyzed using an ARMA model as time series data. Because there was no stationarity in the number of related tweets, we analyzed differences in this number compared with the previous day.

Results: The number of preventive tweets increased by 15.62 tweets (95% CI 4.16, 27.09 p=0.008) during suicide support periods. However, the interday difference in the number of related tweets did

not change significantly during suicide prevention periods (65.98 tweets 95% CI -330.00, 461.96 p=0.744).
Discussion: The ARMA model showed that preventive tweets significantly increased during suicide support periods. It will be necessary in future studies to more closely examine the influence of social media on suicide incidents by linking with external data.

1. Introduction

With the spread of the Internet and social media, these technologies have become an important source for general medical and health information, and its influence has become an area of research attention (Norman, 2011; Lau et al., 2012). In recent years, the impact of social media, which can easily facilitate the sharing of information even among individuals, cannot be ignored today (Norman, 2011; Lau et al., 2012).

In Japan, about 30,000 people committed suicide in the past several decades annually(Ministry of Health Labor and Welfare, 2016). Prevention of suicide is also an important concern. In young people suicide is at the top of the cause of death (World Health Organization, 2014). For suicide prevention for young people, suicide prevention using this platform is beneficial as they use the Internet and social media well. Several studies on suicide prevention have been carried out so far (Woolf, Bantjes & Kagee, 2015; Ross, Kõlves & De Leo, 2016).

In addition, it has been found that reports of suicides by the mass media have influenced suicide numbers in the past, and WHO has issued recommendations about media coverage of suicides (World Health Organization, 2008). Indeed, many researchers have studied the effect of conventional mass media on mental health. In these studies, it is mentioned that negative coverage adversely affects mental health (Corrigan et al., 2005; Dietrich et al., 2006; Song et al., 2016). With this backdrop, information on social media is also understood to play an important role in the dissemination of appropriate information regarding suicides (Jashinsky et al., 2014; Sueki, 2015; Perry et al., 2016; Rice et al., 2016).

Suicide Prevention Week (September 10 to September 16) and Suicide Support Measures Reinforcement Month (March) have been established in Japan, and awareness-raising activities regarding suicide-related issues (such as Government public relations through posters and the Internet, free consultation and so on) are also implemented (Ministry of Health, Labour and Welfare). However, social media information regarding suicides observed during these periods has not been sufficiently examined.

In this study, I aim to clarify whether the numbers of tweets concerning suicide prevention and other tweets related to suicide posted on Twitter change during Suicide Prevention Week and Suicide Support Measures Reinforcement Month.

2. Method and Subjects

2.1. Twitter data source

Kuchikomi@kakaricho (Hotto Link Inc., Tokyo, Japan) was used to obtain the number of postings (tweets) on Twitter (http://www.twitter.com). Kuchikomi@kakaricho is a commercial service that randomly samples 10% of all tweets and that were recorded in a database.

2.2. Extraction of target data

Total tweet figures were extracted from dates between January 1, 2011 and December 31, 2014. Search parameters used are shown in Table 1. Condition (1): tweets including any of the Japanese words for "suicide" or "self-death." Condition (2): In addition to condition (1), tweets containing "Prevention", "Avoidance", "Countermeasure", "Support", "Project", "Symposium", "Conference", "Panel Discussion", or "Discussion" were counted. The number of tweets searched under condition (2) was defined as "the number of preventive tweets" and the number of tweets found under condition (1) minus the number of preventive tweets was defined as "the number of related tweets", and the number of tweets per day was calculated and used as time series data.

In addition to general tweets, Twitter has a "retweet" function used for the purpose of sharing information etc., as well as "reply" and "mention" functions including the user's name, and all of these tweets were extracted.

2.3. Model Descriptions

2.3.1. ARMA model

The autoregressive moving average model is a combination of an autoregressive model (AR) and a moving average model (MA) and is widely used in time series analyses (Box, 1976). ARMA (p, q) can be expressed as a general expression as follows:

$$Y_t = \beta_0 + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{q-t} \quad \text{(Equation 1)}$$

In this study, in order to consider the impact of prevention periods and of remarkable outliers as explained in the next paragraph, I considered dividing the following equation into a structural equation and a disturbance equation (Harvey, 1989; Hamilton, 1994):

$$Y_t = \beta_0 + \beta_1 prevent_t + \beta_2 outlier1_t + \beta_3 outlier2_t + u_t \quad \text{(Equation 2, Structural equation)}$$
$$u_t = \phi_1 u_{t-1} + \cdots + \phi_p u_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \quad \text{(Equation 3, Disturbance equation)}$$

The term "prevent" in the above formula is a variable that represents "1" if *t* is during a preventive period (March or September 10 - September 16). The term "outlier 1" represents "1" if *Yt* is a value equal to or greater than the 95th percentile and less than the 99th percentile of *Y* as a whole and the term "outliner 2" is "1" if *Yt* is greater than or equal to the 99th percentile of the entire *Y*. In all variables of “prevent”, “outlier 1” and “outlier 2”, these represent “0” if they do not correspond to the condition.

2.3.2. Time Series Analysis

The time series analysis was performed based on the following four steps.

First, the stationarity of the time series data was checked using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). ACF and PACF give information on autocorrelation and partial autocorrelation. In lag x, autocorrelation (partial autocorrelation) between one day and x days ago is calculated. In this study, autocorrelation and partial autocorrelation from lag 1 to lag 20 were calculated. When it appeared that the data was nonstationary, it was converted to the interday differences, and the stationarity was checked again.

Next, the values for candidate p and q in the ARMA (p, q) model were determined according to the ACF and PACF. In general, more than one candidate models are selected.

As a third step, goodness of fit of the model was confirmed by performing residual checks based on candidate p and q. If the model is adequate, the residual is equivalent to white noise (average 0, with dispersion not time-dependent). This was examined using the Box-Jenkins Q test (Box & Pierce, 1970). If the *p*-value of the Q statistic is less than 0.9, the candidate model will be determined to be ineligible.

As a fourth step, the Akaike information criterion (AIC) was calculated for the remaining candidate model, and the model with the smallest AIC was selected.

2.4. Statistical analysis

All analyses were conducted using the statistical software package Stata14.2 (StataCorp LP, College Station, TX, USA). For the analyses except Box-Jenkins Q test, a p-value of <0.05 was considered statistically significant.

2.4. Ethical issues

The protocol for this study was reviewed and approved by the Okayama University Graduate School of Medicine, Dentistry and Pharmaceutical Sciences and Okayama University Hospital, Ethics Committee (First approval No. 914, Change approval (change of research period) No. 1013).

3. Results

3.1. Summary of target data

Figure 1 shows the number of preventive tweets and number of other related tweets. This figure also indicates the existence of extreme outliers. Figure 1 (a) shows the transition of prevention tweet. The range of preventive tweets was 0 tweet (March 12, 2011 and May 1, 2011) to 2168 tweets (August 2, 2012). The median was 46 tweets. The range of outlier 1 (95th to 99th percentile) ranged from 175 tweets to 484 tweets, while the outlier 2 (99th percentile or higher) range was 492 tweets to 2168 tweets. Figure 1 (b) shows the transition of the tweet. The range of the related tweet was 57 tweets (January 1, 2011) to 60875 (June 29, 2014). The median was 1637 tweets. The range of outliers 1 was 4010 to 10134, and the range of outliers 2 was 10332 tweets to 60875 tweets.

3.2. Selection of the ARMA model

Figure 2 shows the number of suicide prevention tweets, the number of other related tweets, and ACF and PACF for the interday difference in the number of related tweets. These results were interpreted as follows with reference to Becketti's book (Becketti, 2013).

In Figure 2(a), after the first five lags, autocorrelations were decreasing to near the 95% confidence band. This suggests stationary and $q<6$. In Figure 2(b), the estimated values of the first two partial autocorrelations are 0.446 and 0.013, but the second partial autocorrelation lies within the 95% confidence band. Thus, this graph suggests $p=1$ rather than $p>1$. the ARMA (p, q) model candidate was set with $p = 1$ and $q = 1\text{-}5$ for preventive tweets.

In Figure 2(c), number of related tweets were nonstationary because autocorrelations do not die out. Then, I determined that the number of related tweets was not stationary and used the difference compared with the previous day. In Figure 2(e), after the first two lags, autocorrelations died out. This suggests stationary and $q<3$. In Figure 2(f), the estimated values of the first six and seven partial autocorrelations are -0.106 and -0.044, but the seventh partial autocorrelation lies within the 95% confidence band. Thus, this graph suggests $p<=6$ rather than $p>6$. Regarding the interday difference for other related tweets, $p = 1\text{-}6$ and $q = 1\text{-}2$ were set as ARMA (p, q) model candidates.

Table 2 shows the AICs for the models that were not judged to be ineligible based on results of a Box-Jenkins Q test on the residuals. Because AIC was the smallest, ARMA (1, 2) can be determined to be the optimal model for the number of prevention-related tweets, and ARMA (2, 1) was determined to be the optimal day interday difference for number of related tweets.

3.3. ARMA model estimations

Table 3 shows the parameters estimated by the ARMA model to be the best model after the ARMA model was determined to be optimal. The number of preventive tweets was significantly higher during the prevention periods (15.62 tweets, 95% CI 4.16, 27.09). In contrast, there was no significant relationship between interday differences with regard to -related tweets (65.98 interday differences 95% CI -330.00, 461.96).

4. Discussion

In this study, the ARMA model showed that the number of postings made on Twitter concerning suicide prevention during the suicide prevention periods increased significantly, by 15.62. Because this research data was the result of a 10% sample, this indicates that there was an approximate increase of 150 tweets.

The background surrounding this increase may have been that some healthcare workers have begun using Twitter, and these users were taking measures against suicide, while others were acting to raise awareness and appropriate understanding of suicide during these periods. It is believed that preventive tweets are on the rise because of these individuals' activities.

Meanwhile, the average number of preventive tweets was low at 67.3 tweets per day. Mean values during the preventive period from 2011 to 2014 were 20.0 tweets, 124.8 tweets, 77.4 tweets, and 143.8 tweets, respectively. It is increasing compared to 2011, but not much. and it cannot be said that awareness-raising and educational tweeting activity done on Twitter is widespread overall.

The relevance of Twitter and health-related topics has been reported on with regard to its usefulness in connection with responses to infectious diseases such as influenza (Chew & Eysenbach, 2010) and vaccination (Love et al., 2013; Radzikowski et al., 2016). Regarding suicide and mental illness, it has been reported that social media outlets such as Twitter can become a kind of surveillance system, and it is expected to become a tool of immediacy (Jashinsky et al., 2014; Reavley & Pilkington, 2014; Sueki, 2015).

In this way, while the Internet and social media are seen as useful tools for obtaining information on diseases, in contrast, problems such as the spread of misinformation or excessive search engine optimization (SEO) can arise, and in Japan, major curation media is being closed de facto (DeNA Co Ltd, 2016). It has also been suggested that improving health literacy requires making accurate health information more available through social media and the Internet (Norman, 2011; Mesko, Gyorffy & Kollár, 2015; Fredriksen, Harris & Moland, 2016; Mackert et al., 2016; James & Harville, 2016).

Under these circumstances, the number of preventive tweets increased only during the suicide prevention periods, and related tweets exhibited no significant fluctuations. These observations suggest that Twitter in Japan maintains a certain level of accuracy as a tool for obtaining suicide prevention information.

The findings obtained in this study were the first to capture fluctuations in the information spread through social media during suicide prevention periods to the extent of the author's knowledge, and it is expected that these findings will become important knowledge when considering future suicide prevention measures.

However, there were some serious limitations to this study. First, it is possible that the collected tweets were not collected accurately, and some tweets related to suicide may have been missed. For example, messages using ASCII art or net slang could not be extracted. Next, the number of tweets had extreme outliers, and it was difficult to examine their stationarity. As such, the ARMA model constructed in this study may not be optimal. Further, we were unable to consider the relationship with actual data regarding the number of suicides.

In the future, it will be necessary to refine my time series model while considering outliers and periodicity. It will also be necessary to merge with other statistical data related to suicide and to more directly examine the impact of social media on suicide.

5. Conclusion

The results of this study support the conclusion that the number of tweets posted with the intention of suicide prevention increases significantly during suicide prevention periods, but there are no significant fluctuations in the number of other suicide-related tweets.

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Competing Interests

The author has no conflicts of interest to declare.

Author Contributions

Toshinaru Mitsuhashi conceived and designed the study plan, collected and analyzed the data, contributed analysis software, wrote the paper, prepared figures and tables, reviewed drafts of the paper.

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Table 1. Tweet search conditions used in this study

Definitions	Condition number	Search keywords/search parameters
	Condition (1)	“Suicide” OR “Self-death”
Number of preventive tweets	Condition (2)	Condition (1) AND (“prevention” OR “avoidance” OR “countermeasures” OR “support” OR “project” OR “symposium” OR “conference” OR “panel discussion” OR “discussion”)
Number of related tweets		Tweets from search parameter (1) excluding search parameter (2)

Table 2. AIC for each candidate model

Number of preventive tweets		Interday difference in number of related tweets	
Model	AIC	Model	AIC
ARMA(1,2)	15841.87	ARMA(2,1)	26008.65
ARMA(1,3)	15842.99	ARMA(2,2)	26009.91
ARMA(1,4)	15844.97	ARMA(3,1)	26009.98
ARMA(1,5)	15846.87	ARMA(3,2)	26011.73
		ARMA(4,1)	26011.32
		ARMA(4,2)	26013.32
		ARMA(5,1)	26013.29
		ARMA(5,2)	26015.28
		ARMA(6,1)	26015.25
		ARMA(6,2)	26017.23

Table 3. Results of ARMA model estimation

Number of preventive tweets				
	Coef.	95%CI		p
Structural equation				
Prevention periods	15.62	4.16	27.09	0.008
Outlier1（top 95%〜99%）	170.40	159.30	181.49	0.000
Outlier2（> top 99%）	764.29	755.54	773.03	0.000
Constant	44.91	-15.99	105.82	0.148
Disturbance equation				
AR（auto-regressive）				
Lag1.	1.00	0.99	1.00	0.000
MA（mean-average）				
Lag1.	-0.95	-0.98	-0.92	0.000
Lag2.	-0.01	-0.04	0.02	0.412

Interday difference in number of related tweets				
	Coef.	95%CI		p
Structural equation				
Prevention periods	65.98	-330.00	461.96	0.744
Outlier1（top 95%〜99%）	1122.11	506.24	1737.98	0.000
Outlier2（> top 99%）	6084.80	5544.43	6625.17	0.000
Constant	-112.51	-232.99	7.97	0.067
Disturbance equation				
AR（auto-regressive）				
Lag1.	0.30	0.27	0.34	0.000
Lag2.	-0.05	-0.07	-0.04	0.000
MA（mean-average）				
Lag1.	-0.68	-0.72	-0.64	0.000

Figure 1.(a) Fluctuations in the time series for number of preventive tweets

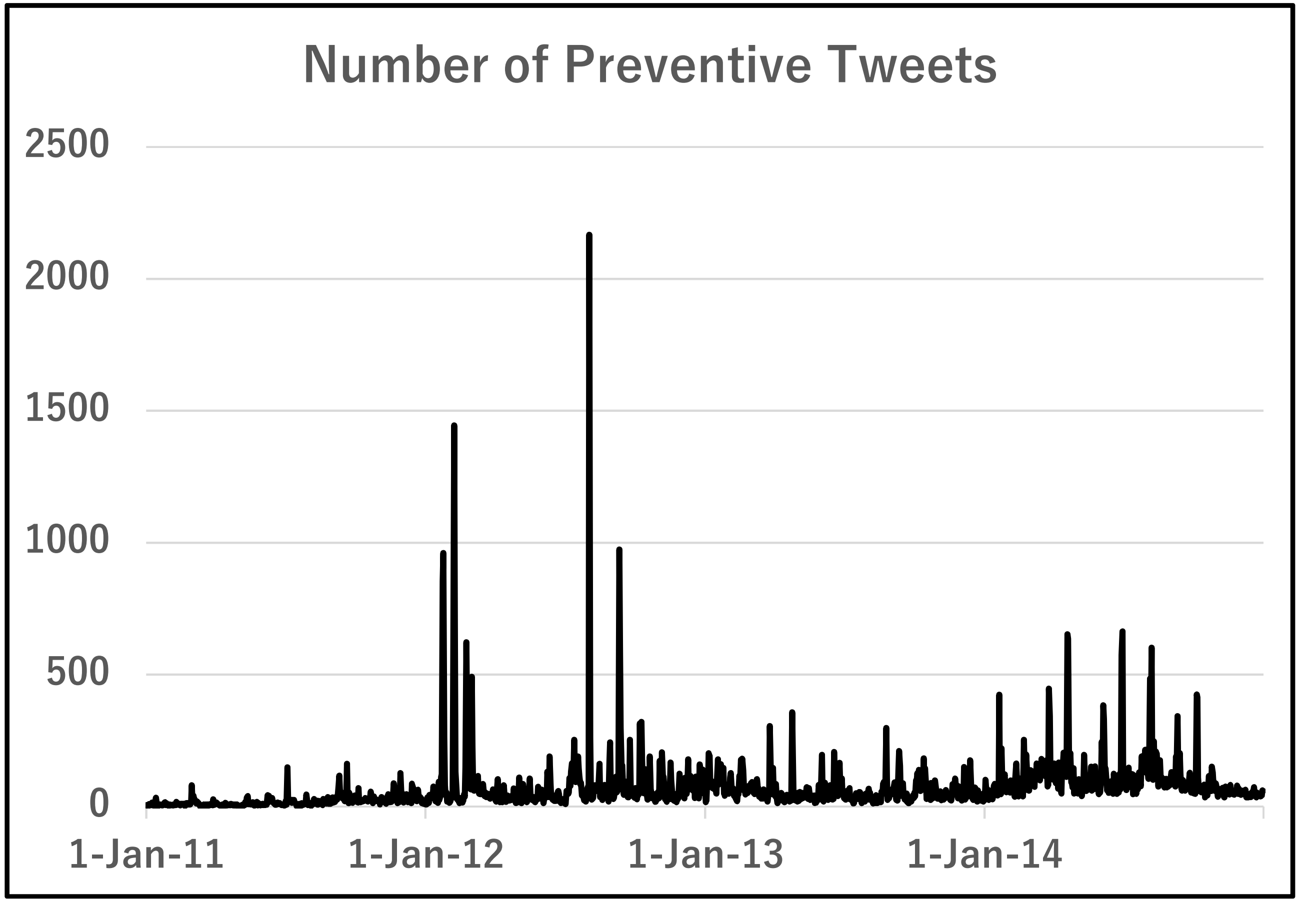


Figure 1(b). Fluctuations in the time series for related tweets

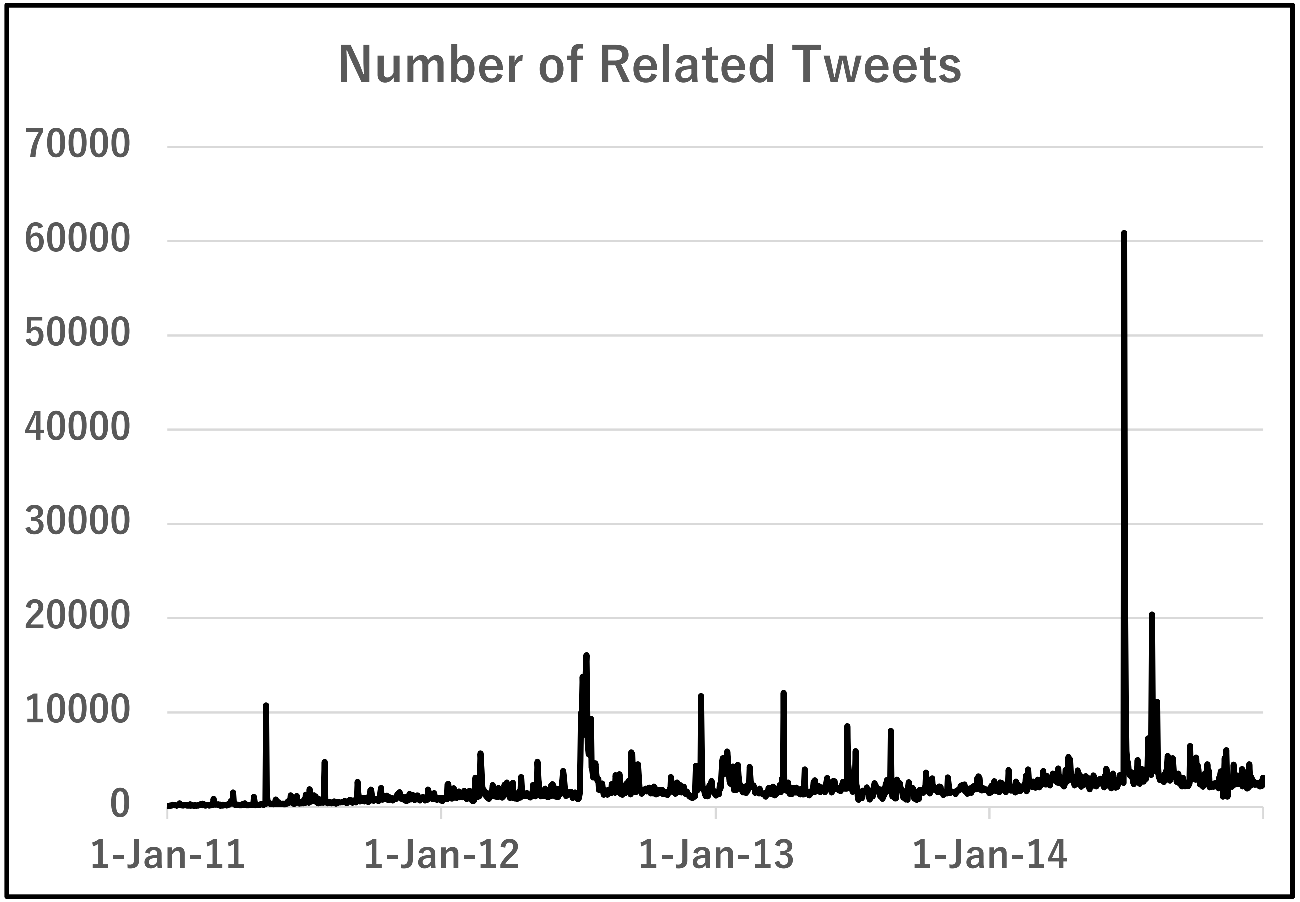
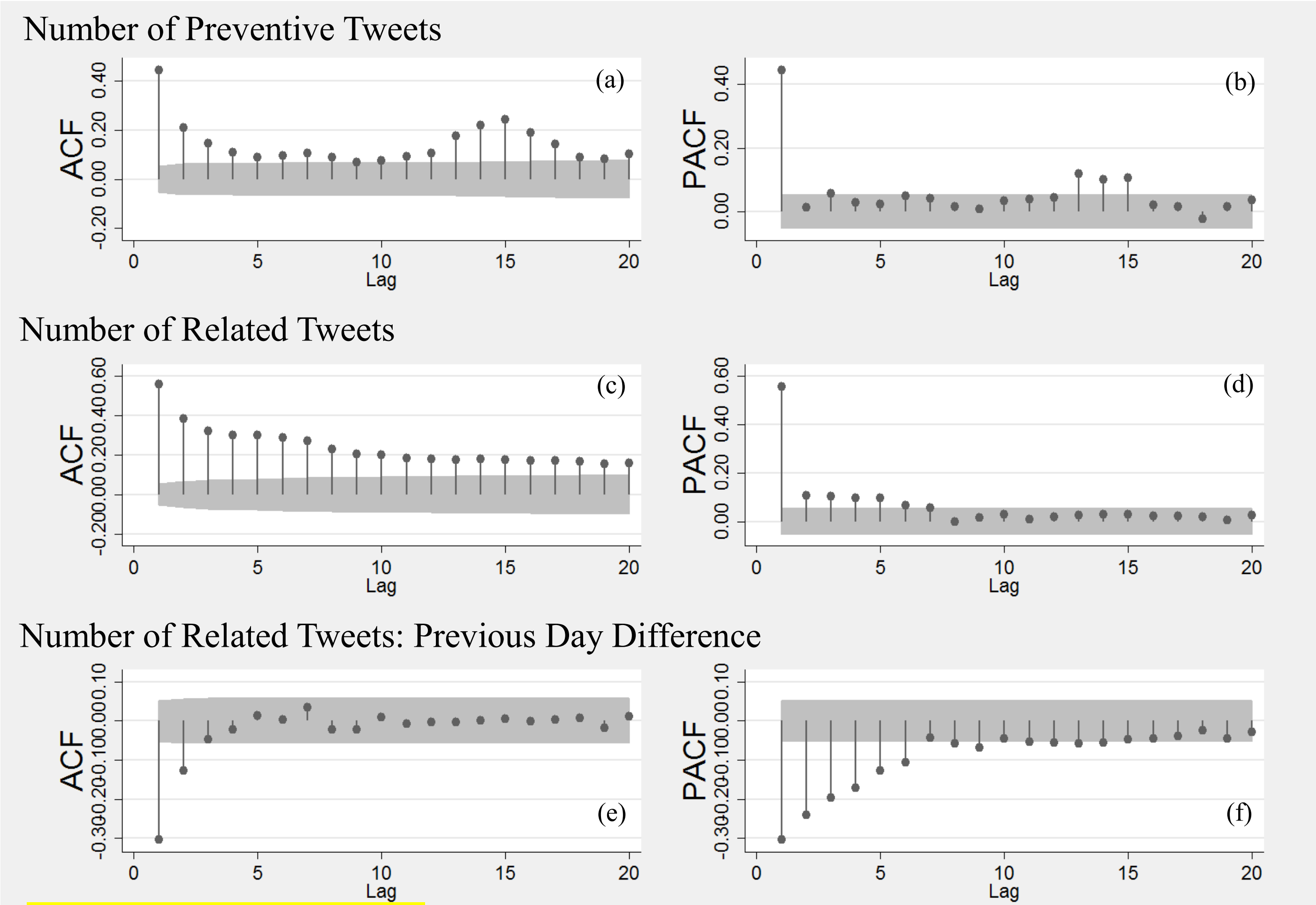


Figure 2. ACF and PACF for number of preventive tweets, number of related tweets, and the interday difference in the number of related tweets



The gray zone: 95% confidence band.