Reports of Own and Others’ Symptoms and Diagnosis on Social Media Predict COVID-19 Case Counts in Mainland China

Cuihua Shen¹*, Anfan Chen²*, Chen Luo³, Wang Liao¹, Jingwen Zhang¹, Bo Feng¹

1. University of California, Davis
2. University of Science and Technology of China
3. Tsinghua University
* Equal contribution

Corresponding Author: Cuihua Shen, Department of Communication, UC Davis, One Shields Ave, Davis, CA, 95616, USA. cuishen@ucdavis.edu

Abstract

Can public social media data be harnessed to predict COVID-19 case counts? We analyzed more than 12 million COVID-19 related posts on Weibo, a popular Twitter-like social media platform in China, from November 20, 2019 to March 3, 2020. We developed a machine learning classifier to identify “sick posts,” which are reports of one’s own and other people’s symptoms and diagnosis related to COVID-19. We then modeled the predictive power of sick posts and other COVID-19 posts on daily case counts. We found that reports of symptoms and diagnosis of COVID-19 significantly predicted daily case counts, up to seven days ahead of official statistics. But other COVID-19 posts did not have similar predictive power. For a subset of geotagged posts (2.85% of all retrieved posts), we found that the predictive pattern held true for both Hubei province and the rest of mainland China, regardless of unequal distribution of healthcare resources and outbreak timeline. Researchers and disease control agencies should pay close attention to the social media infosphere regarding COVID-19. On top of monitoring overall search and posting activities, it is crucial to sift through the contents and efficiently identify true signals from noise.

Keywords: COVID-19, SARS-CoV-2, novel coronavirus, social media, Weibo, China, disease surveillance
Introduction

Since the outbreak of COVID-19 in December, 2019, in Wuhan, Hubei Province, China,\textsuperscript{1,2} the novel coronavirus has already affected 203 countries and territories worldwide. As of April 2, 2020, there were around 1 million confirmed cases and more than 50,000 deaths.\textsuperscript{3} Amid many unknowns, severe lack of laboratory testing capacity, delays in case reports, variations in local COVID-19 responses, and uncoordinated communication pose tremendous challenges for monitoring the epidemic dynamics and developing policies and targeted interventions for resource allocation.

When conventional disease surveillance capacity is limited, publicly available social media data can play a crucial role in uncovering hidden dynamics of an emerging outbreak.\textsuperscript{4} Past research has shown social media activities can predict disease transmission and outbreaks before conventional surveillance methods, with the majority focusing on modeling influenza epidemics and relying on coarse-grained data retrieved from keyword searches.\textsuperscript{5-10} The unprecedented magnitude and transmission speed of COVID-19 also brought about massive social media activities as people isolate in their homes to break the infection chains.\textsuperscript{11} Massive social media data inevitably contain massive noise (e.g., public reactions and awareness of the disease), which can be counterproductive for disease forecasting.\textsuperscript{5} It is therefore critical to identify reliable signals (e.g., sick posts reporting symptoms and diagnosis) to predict infection cases and inform a rapid response.\textsuperscript{12}

Here we present an effort to collect and analyze COVID-19 related posts on the most popular public social media site in China, Weibo. To our knowledge, this is the first study that examines a large and fine-grained dataset of 12 million social media posts to predict COVID-19 case counts in China from November 20, 2019 to March 3, 2020. With much increased data granularity, we developed a supervised machine-learning classifier to distinguish “sick posts,” which are reports of own and others’ self- and other-reports of symptoms and diagnosis, from other COVID-19 related posts that could dilute disease signals from the data stream. Using the officially reported case accounts as the outcome, we compared the predictive power of sick posts versus other COVID-19 posts. We show evidence that sick posts predict China CDC’s daily case counts up to seven days in advance, while other COVID-19 related posts do not have similar predictive power. For the subset of geotagged posts, we found that the predictive pattern held true for both Hubei province and the rest of mainland China.

Methods

Data Collection

Social media data used in this study were collected from a popular Chinese microblog platform, Weibo. With over 462 million monthly active users in 2018,\textsuperscript{13} Weibo is very similar to
Twitter, the access to which is blocked in mainland China. Unlike Twitter, Weibo does not provide public API access to its database. Keywords-based advanced search of Weibo posts is allowed via its web interface; however, the output of such searches is limited to 50 pages (or around 500 posts) as per Weibo policy, making large-scale public data access notoriously difficult. To bypass these limitations, we retrieved posts from a user pool maintained by our research team (see SI section A). The pool consists of about 250 million users (with bots filtered out), which are approximately 54% of all monthly active Weibo users in 2018 and similar to the population of Weibo users at that time in terms of sex and age distribution (see Figure 1).

![Sex and Age Distribution](image)

*Figure 1* Demographic composition of our Weibo user pool with 2018 Annual Sina Weibo user report

**COVID-19 posts**

We retrieved COVID-19 posts by searching through all posts by users in the user pool, with a list of 167 keywords covering generally related terms such as coronavirus and pneumonia, as well as specific locations (e.g., “Wuhan”), drugs (e.g., “remdesivir”), preventive measures (e.g., “mask”), among others (see SI Table S1 for a complete list). After removing duplicates (i.e., reposts of original posts), we retained 12,884,074 posts sent between November 20th, 2019 (i.e., 10 days before the first confirmed cases) and March 3rd, 2020. A fraction of these posts (2.85%; N = 367,189) were tagged with geographic information and we distinguished between posts sent within Hubei province (i.e., the epicenter; N = 126,998) and those from elsewhere in Mainland China (N = 240,191).

**Sick Posts**
We define “sick posts” as posts that report any symptoms and/or diagnoses that are likely related to COVID-19 based on published research and news reports from medical social media site DXY.cn. We collected a broad list of symptoms, including common symptoms such as cough and shortness of breath, and uncommon symptoms such as diarrhea. Sick posts can be further categorized into “ingroup sick posts,” which disclose one's own or immediate family members' symptoms or diagnoses, and “outgroup sick posts” which report those from other people not in one’s immediate family. We list one example of “ingroup sick post” and one for “outgroup sick post” below (translated and edited for brevity):

“During the SARS epidemic in 2003, I got pneumonia with symptoms of fever and cough, was suspected of being infected with SARS, and ended up being hospitalized for more than a month. Now we got COVID-19 in 2020 and I started coughing again, which has lasted for more than a month. What a mess <Face Palm>” (posted at 10:23 p.m., January 29th, 2020)

“One man in another village drank too much. He said he felt sick and had cold symptoms. His brother measured his temperature which turned out to be 38 Celsius. His brother called 120 and sent him to hospital. The whole village was shocked and everyone was afraid to go outside. “(posted on 10:14 pm, January 29th, 2020)

We used supervised machine learning to identify sick posts from the 12 million COVID-19 posts. We first sampled 11,575 posts evenly across the 94 days of COVID-19 posts. Next, 11 human judges annotated whether a post was an “ingroup sick post,” “outgroup sick post,” or “other COVID-19 post.” The judges independently annotated a subset of 138 posts and achieved high agreement (Krippendorff’s \( \alpha = 0.945 \)) before they divided and annotated the remaining posts. Then, the annotated posts were used to train machine learning models with various algorithms (i.e., decision tree, extra tree, extra trees, random forest, k-nearest neighbor, multi-layer perceptron, and support vector machine). Based on the classification performance (see SI Table S2), we selected the model using the random forest algorithm (F1 score = .880). Finally, the model automatically classified all COVID-19 posts into 344,284 “ingroup sick posts,” 93,951 “outgroup sick posts,” and 12,445,839 “other COVID-19 posts.” Because of the scarcity of outgroup sick posts, we combined ingroup and outgroup sick posts in subsequent analyses.

In addition, 4,376 sick posts and 122,622 other COVID-19 posts were tagged in Hubei, and 19,293 sick posts and 220,898 other COVID-19 posts were from elsewhere in Mainland China. These post counts were then aggregated by days. To control for the general growth of Weibo posts, we further normalized these numbers against the daily counts of all posts in our pool. The normalized counts can be interpreted as counts per 10-million posts. Figure 2 illustrates our data collection and classification process.
We collected daily new case counts in Mainland China from China CDC on March 23rd, 2020. China CDC’s official website started collating data from January 16th, 2020. Earlier counts were obtained from Huang et al.\(^1\) and validated against relevant briefings from the National Health Commission. The final data covers the period from December 1st, 2019, to March 3rd, 2020, and we also distinguished between the cases within and outside Hubei (see Figure 3).
It is noteworthy that on February 12, 2020, a set of less conservative diagnosis criteria were implemented and led to a temporary surge of new cases. The incidence’s impact was controlled in our analysis, as described below.

**Statistical Analysis**

We performed Granger causality tests to discover if the increase of sick posts statistically predicts the increase of confirmed cases, as formulated in the following linear model:

\[ \Delta C_t = a_0 + \sum_{i=1}^{m} a_i \Delta C_{t-i} + \sum_{j=1}^{m} b_j \Delta S_{t-j} + c_1 I_t + \epsilon_t \]

where \( C_t \) is the difference of new case counts at day \( t \) from day \( t-1 \), \( S_t \) the difference of sick post counts (normalized) at day \( t \) from day \( t-1 \), and \( I_t \) is a time-varying binary variable that equals 1 on February 12th, 2020, on which day China CDC changed the diagnostic criteria. This binary variable controls for the exogenous pulse of case counts.

Difference scores are used because the Dickey-Fuller test (including 10 lagged differences) suggests the new case counts are non-stationary \( (p = .413) \), so are the sick post counts \( (p = .527) \), both violating the assumption of testing Granger causality using linear models. Dickey-Fuller tests suggest the difference scores restore the stationarity of new case counts \( (p = .025) \) and daily sick post counts \( (p = .008) \). These difference scores can be interpreted as “daily-additional” new cases and sick posts on top of the counts from the previous day.

**Results**

The final dataset includes daily observations \( (N = 94) \) of the national level confirmed case counts, sick post counts (normalized), and other COVID-19 post counts (normalized), as well as these counts within and outside of Hubei Province. Daily counts of Weibo posts and new cases over time are illustrated in Figure 3.
Figure 3. Daily social media posts and lab-confirmed cases between November 20th, 2019 and March 3rd, 2020

We estimated the aforementioned linear model with 10 lagged terms for both the new case counts and sick post counts. Figure 4(A) summarizes estimates of the sick post counts’ Granger causality on daily case counts (see SI Table S3). Particularly, one unit increase in the normalized sick post counts (i.e., 1 sick post per 10-million posts) predicted 1.252 (95% CI: 0.308, 2.196) to 3.885 (95% CI: 2.227, 5.543) daily-additional new cases 1 to 7 days in the future.
Figure 4. Granger causality coefficient estimates (with 95% CIs based on robust standard errors) for time-lagged sick posts and other COVID-19 posts predicting daily additional case counts.

To corroborate the above results, we performed additional analyses. First, we tested the relationship between new case counts and other COVID-19 post counts (normalized), using the same linear model. Figure 4(A) further illustrates the estimates such that other COVID-19 post counts had limited predictive power on future new case counts. Their effect size ($\eta^2 = .224$) was also smaller than that of the sick post counts based on the aforementioned model ($\eta^2 = .614$, see SI Table S4). It means that Weibo posts that discuss some aspect of COVID-19, but did not report anyone’s symptoms or diagnosis, could only predict future case counts to a very limited degree.

Second, we tested the sick post counts’ Granger causality within Hubei and outside of Hubei (SI Table S3). Inside Hubei, the results largely agree with the national results mentioned before, such that daily-additional sick post counts predicted future additional new case counts...
within this province for 2 to 7 days in advance, as illustrated in Figure 4(B). The estimated coefficients of these effects were much larger than those at the national level, although they explained less variance of the case counts. This is plausible since these geo-tagged posts were only a small fraction of all sick posts. Outside Hubei, fewer lag terms of sick-post ratios were statistically significant but still demonstrated a similar pattern (see Figure 4(C)).

Finally, as a robustness check, we tested the reversed Granger causality of new cases on future sick posts, using a vector autoregression model (see SI Table S5-S6). The predictive effect of cases on sick posts is much weaker than the that of sick posts on cases: Only 3 out of the 10 lagged terms for new cases had statistically significant effects, and the 10 terms together had a smaller effect size ($\eta^2 = .259$) compared with that of the autoregressive terms for the sick post counts themselves ($\eta^2 = .360$).

### Discussion

The novel coronavirus causing COVID-19 is a pathogen new to the human reservoir. It poses an extraordinary challenge for public health systems worldwide, because screening and diagnostic tests have to be developed from scratch. Even when such tests eventually become available, testing capacity is often severely limited, fueling the outbreak as many patients unknowingly infect others. Based on more than 12 million COVID-19-related Weibo posts between November 20, 2019 and March 3, 2020, we developed a supervised machine learning classifier to identify “sick posts,” which are reports of one’s own and other people’s symptoms and diagnosis of COVID-19. Using the officially reported daily case counts as the outcome, our work shows that sick posts significantly predict daily case counts, up to seven days ahead of official statistics. This finding confirms prior research that social media data can be usefully applied to nowcast and forecast emerging infectious diseases such as COVID-19.\(^{18, 19}\)

Our finding that other COVID-19 posts do not have similar predictive power as that of sick posts shows that not all social media data are equally informative. Specifically, COVID-19 has dramatically disrupted everyday life, resulting in people sheltering in place and increasingly communicating with others via social media. As shown in our dataset, the majority of COVID-19 chatter on Weibo was due to public awareness of COVID-19, rather than actual symptom reports. When facing a deluge of social media activities as a result of COVID-19 mitigation measures, the primary challenge in using social media for disease surveillance is to identify valid signals from noise.\(^{12, 19-21}\) Most previous work took rather coarse-grained approaches, relying primarily on keyword searches. Our work demonstrates one viable way to identify the signal through reports of symptoms and diagnosis, bringing significant contributions to the literature on digital surveillance.

Another important finding is that the predictive power of sick posts on daily case counts holds true for both Hubei and non-Hubei regions, but the effect sizes vary. Being the epicenter of
the outbreak, Hubei province experienced extreme testing shortage during the early stage of the study period. As a result, many Hubei residents turned to social media sites such as Weibo to seek help for testing and medical care. By contrast, social media help-seeking activities were uncommon in other parts of China where testing and healthcare resources were much more adequate. With such regional variations, we still observe strong signals of sick posts’ prediction on case counts, suggesting the predictive power of sick posts was robust against testing delays. Further, the variations in effect sizes show that social media data’s predictive power may vary across different geographic areas, with different levels of preparedness, and at different stages of the outbreak. Future studies based on longer periods of data monitoring could explore in more depth the temporal and spatial variations of COVID-19 social media surveillance efficacy.

Our work has broad public health implications. The high speed and low cost of social media surveillance can be especially useful at the early stages of the COVID-19 outbreak, to inform containment and mitigation efforts when they are most cost-effective. For countries and regions where public health infrastructures do not allow for widespread screening and diagnostic tests, social media disease surveillance provides much needed information for public health agencies to model the trajectories of the outbreak, and make swift decisions about resource allocation, such as hospital beds, ventilators, and personal protective equipment.

Another advantage of social media surveillance is that it can be done from afar. As COVID-19 continues to spread across the globe, countries lacking testing and screening infrastructures will become “dark spots,” endangering their own people as well as the entire world. It is imperative that international organizations such as the World Health Organization integrate such data into their outbreak forecasting management practices, in order to mobilize and coordinate relief efforts to help combat COVID-19.

This study has a number of limitations. First, Weibo posts were retrieved retrospectively, rather than in real-time, which means deleted or censored posts were absent from our dataset. However, we have no reason to believe that deletion or censorship favored “sick posts” in measurable ways, therefore our results should be unaffected by these omissions. Second, as some studies suggest,\textsuperscript{22-24} confirmed COVID-19 case counts published by China CDC may be a significant underestimation of the actual counts, due in part to limits in testing capacity and the existence of asymptomatic carriers. Still, the data here represents the best known data of confirmed case counts.

The threats of COVID-19 and other infectious diseases are likely to recur in the future. Reports of symptoms and diagnosis on social media during emerging disease outbreaks send invaluable warning signals to the public. Researchers and disease control agencies should pay close attention to the social media infosphere. On top of monitoring overall search and posting activities, it is crucial to sift through the contents and efficiently identify true signals from noise. Our main findings highlight the importance of using rigorous procedures to obtain quality signals
to quantify sickness reports. Future studies based on longer periods of data monitoring could explore in more depth the time and spatial diffusion of COVID-19. More detailed examination of post contents reporting restraints in information or medical resources will be helpful in developing local outbreak responses.

Acknowledgements

We thank Jingyang Xu, Minwei Ren, Rixia Tang, Zichao Wang, Yongyan Xu, Na yang, Yalan Jin, Xiuchan Xu, Xinyu Wang, Ruizhi Sun, Wenhui Zhu, Yiwei Li, Tianyu Zhao for their help with data annotation.

References

1. Huang C, Wang Y, Li X, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. The Lancet 2020; 395(10223): 497-506.
2. Wu F, Zhao S, Yu B, et al. A new coronavirus associated with human respiratory disease in China. Nature 2020; 579(7798): 265-9.
3. World Health Organization. Coronavirus disease 2019 (COVID-19) Situation Report 74, 2020.
4. Zhang J, Centola D. Social Networks and Health: New Developments in Diffusion, Online and Offline. Annual Review of Sociology 2019; 45(1): 91-109.
5. Aiello AE, Renson A, Zivich PN. Social Media– and Internet-Based Disease Surveillance for Public Health. Annual Review of Public Health 2020; 41(1): 101-18.
6. Charles-Smith LE, Reynolds TL, Cameron MA, et al. Using Social Media for Actionable Disease Surveillance and Outbreak Management: A Systematic Literature Review. PloS one 2015; 10(10): e0139701-e.
7. Zhang EX, Yang Y, Di Shang R, et al. Leveraging social networking sites for disease surveillance and public sensing: the case of the 2013 avian influenza A(H7N9) outbreak in China. Western Pac Surveill Response J 2015; 6(2): 66-72.
8. Guo P, Zhang Q, Chen Y, et al. An ensemble forecast model of dengue in Guangzhou, China using climate and social media surveillance data. Science of The Total Environment 2019; 647: 752-62.
9. Cui X, Yang N, Wang Z, et al. Chinese social media analysis for disease surveillance. Personal and Ubiquitous Computing 2015; 19(7): 1125-32.
10. Fung IC-H, Fu K-W, Ying Y, et al. Chinese social media reaction to the MERS-CoV and avian influenza A(H7N9) outbreaks. Infectious Diseases of Poverty 2013; 2(1): 31.
11. Li L, Zhang Q, Wang X, et al. Characterizing the Propagation of Situational Information in Social Media During COVID-19 Epidemic: A Case Study on Weibo. IEEE Transactions on Computational Social Systems 2020; 7(2): 556-62.
12. Broniatowski DA, Paul MJ, Dredze M. National and local influenza surveillance through Twitter: an analysis of the 2012-2013 influenza epidemic. PloS one 2013; 8(12): e83672-e.
13. Sina. 2018 Annual Sina Weibo User Report. 2019. https://data.weibo.com/report/reportDetail?id=433.
14. Sun K, Chen J, Viboud C. Early epidemiological analysis of the coronavirus disease 2019 outbreak based on crowdsourced data: a population-level observational study. *The Lancet Digital Health* 2020; 2(4): e201-e8.
15. China CDC. China CDC COVID-19 Situation Report on February 12, 2020, 2020.
16. Granger CWJ. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica* 1969; 37(3): 424-38.
17. Box GEP, Tiao GC. Intervention Analysis with Applications to Economic and Environmental Problems. *Journal of the American Statistical Association* 1975; 70(349): 70-9.
18. Li C, Chen LJ, Chen X, Zhang M, Pang CP, Chen H. Retrospective analysis of the possibility of predicting the COVID-19 outbreak from Internet searches and social media data, China, 2020. *Euro Surveill* 2020; 25(10): 2000199.
19. Buckee C. Improving epidemic surveillance and response: big data is dead, long live big data. *The Lancet Digital Health* 2020.
20. Hua J, Shaw R. Corona Virus (COVID-19)“Infodemic” and Emerging Issues through a Data Lens: The Case of China. *International Journal of Environmental Research and Public Health* 2020; 17(7): 2309.
21. Leung GM, Leung K. Crowdsourcing data to mitigate epidemics. *The Lancet Digital Health* 2020; 2(4): e156-e7.
22. Kucharski AJ, Russell TW, Diamond C, et al. Early dynamics of transmission and control of COVID-19: a mathematical modelling study. *The Lancet Infectious Diseases* 2020.
23. Imai N, Dorigatti I, Cori A, Donnelly C, Riley S, Ferguson NM. Report 2: Estimating the potential total number of novel Coronavirus cases in Wuhan City, China, 2020.
24. Wu JT, Leung K, Leung GM. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. *The Lancet* 2020; 395(10225): 689-97.
Reports of Own and Others’ Symptoms and Diagnosis on Social Media Predict COVID-19 Case Counts in Mainland China

Supplementary Information

Cuihua Shen1*, Anfan Chen2*, Chen Luo3, Wang Liao1, Jingwen Zhang1, Bo Feng1

4. University of California, Davis
5. University of Science and Technology of China
6. Tsinghua University
* Equal contribution

Below we provide additional details on the Weibo user pool we built, the keywords we used to retrieve COVID-19 Weibo posts, the detailed results of machine learning models, the summary tables of vector autoregression models, the summary tables of OLS models, as listed below:

A. Weibo User Pool
B. Table S1. Covid-19 related keywords used to retrieve Weibo posts
C. Table S2: Extended metrics for evaluating the performance of classifiers constructed by machine learning for ingroup sick posts
D. Table S3: Summaries of daily difference of new case numbers regressed on daily differences of sick post numbers (N = 94)
E. Table S4: Summaries of daily difference of new case numbers regressed on daily differences of other Covid-19 post numbers (N=94)
F. Table S5: Vector autoregression results of daily difference of new case numbers and daily difference of sick post numbers (N=94)
G. Table S6: Vector autoregression results of daily difference of new case numbers and daily difference of other Covid-19 post numbers (N = 94)
A. Weibo User Pool

Unlike Twitter, Weibo does not provide public API access to its database. Keywords-based advanced search of Weibo posts is allowed via its web interface; however, the output of such searches is limited to 50 pages (or around 500 posts) as per Weibo policy, making large-scale public data access notoriously difficult. To bypass these limitations, we built a Weibo user pool, which started from 5 million active Weibo users obtained in our previous research unrelated to COVID-19, during July 1, 2018 and December 12, 2018. We then retrieved the initial users’ followers and followees (2nd degree users), the followers and followees of the 2nd degree users (3rd degree users), and so forth until no new users were found, resulting in a pool of 250 million users (approx. 54% of all monthly active Weibo users in 2018).

B. Table S1. Covid-19 related keywords used to retrieve Weibo posts

The list was generated following the best practices in content retrieval and analysis (Lacy, Watson & Lovejoy, 2015). Particularly, we closely observed Weibo posts daily from late January to early March 2020, and selected 167 keywords.

| Keyword                        | Translation                        |
|-------------------------------|------------------------------------|
| 武汉肺炎                      | Wuhan pneumonia                    |
| 新型冠状病毒肺炎               | COVID-19                            |
| 不明原因肺炎                  | Pneumonia of unknown cause         |
| 肺炎疫情                      | Pneumonia outbreak                 |
| 野味肺炎                      | Wildlife pneumonia                 |
| 新型冠状病毒 AND 确诊             | Novel coronavirus AND Confirmed infected |
| 感染人数                      | Number of infected cases           |
| 出门 AND 戴口罩                | Going out AND Wear mask            |
| N95 AND 口罩                   | N95 AND Mask                       |
| 3M AND 口罩                    | 3M AND Mask                        |
| KN95 AND 口罩                  | KN95 AND Mask                      |
| 大众畜牧野味店                 | Dazhong wildlife restaurant        |
| 口罩                          | Mask                               |
| 新肺炎                        | Novel pneumonia                    |
| 华南野生市场                  | South China wild market            |
| 冠状肺炎                      | Corona pneumonia                   |
| 武汉病毒所                    | Wuhan Institute of Virology        |
| China AND CDC                  | China AND Center for Disease Control and Prevention |
| 中国疾控预防控制中心          | Chinese Center for Disease Control and Prevention |
| #2019nCoV                     | ...                                |
| 双黄连 AND 抢购                | Shuanghuanglian AND Rush to buy    |
| 双黄连 AND 售罄                | Shuanghuanglian AND Sold out       |
| 武汉卫健委                    | Wuhan Municipal Health Committee   |
| 湖北卫健委                    | Health Commission of Hubei Province |
| 肺炎                          | Pneumonia                          |
| 疫情                          | Epidemic outbreak                  |
| 隔离                          | Quarantine                         |
| 火神山                        | Huoshen Shan hospital              |
| 雷神山                        | Leishen Shan hospital              |
| 钟南山                        | Zhong Nanshan                      |
| 疫情防控                      | Epidemic prevention and control    |
| Coronavirus                    | ...                                |
| Remdesivir                     | ...                                |
| 瑞德西韦                       | Remdesivir                         |
| 新型肺炎 AND 死亡              | Novel coronavirus pneumonia AND Death |
| 新型肺炎 AND 感染              | Novel coronavirus pneumonia AND Infection |
| 新型冠状病毒 AND 感染           | Novel coronavirus AND Infection    |
| 感染 AND 案例 | Infected AND Cases |
| 武汉 AND 封城 | Wuhan AND Lockdown |
| 高福 | George Fu Gao |
| 王延轶 | Wang Yanyi |
| 舒红兵 | Shu Hongbing |
| 协和医院 | Xiehe Hospital |
| 武汉 AND 隔离 | Wuhan AND Quarantine |
| 医生 AND 李文亮 | Doctor AND Li Wenliang |
| 云监工 | Supervising work on cloud |
| 武汉 AND 肺炎 AND 谣言 | Wuhan AND Pneumonia AND Rumors |
| 8 名 AND 散布武汉肺炎谣言 | Eight people AND Spread rumors of Wuhan pneumonia |
| 武汉仁爱医院 | Wuhan Ren'ai Hospital |
| 黄冈 AND 新肺炎 | Huanggang AND Novel pneumonia |
| 黄冈 AND 新型冠状病毒 | Huanggang AND Novel coronavirus |
| 黄冈 AND 感染者 | Huanggang AND Infected cases |
| 孝感 AND 新肺炎 | Xiaogan AND Novel pneumonia |
| 孝感 AND 新型冠状病毒 | Xiaogan AND Novel coronavirus |
| 孝感 AND 感染者 | Xiaogan AND Infected cases |
| 居家隔离 | Isolated at home |
| 隔离 AND 14 天 | Isolation AND 14 days |
| 潜伏期 AND 24 天 | Incubation period AND 24 days |
| 潜伏期 AND 14 天 | Incubation period AND 14 days |
| 新肺炎 | Novel pneumonia |
| 新型冠状病毒 | Novel coronavirus |
| 国际公共卫生紧急事件 | International Public Health Emergencies |
| PHEIC | International Public Health Emergencies |
| #nCoV | ... |
| 方舱医院 | FangCang Hospital |
| 一省包一市 | One province gives a hand to one Hubei city |
| 新冠肺炎 | Novel coronavirus pneumonia |
| 晋江毒王 | Super spreader of COVID-19 in Jinjiang |
| 超级传播者 | Super spreader |
| 湖北 AND 王晓东 | Hubei AND Wang Xiaodong |
| 蒋超良 | Jiang Chaoliang |
| #武汉肺炎 | #Wuhan pneumonia |
| 武汉 AND 李文亮 | Wuhan AND Li Wenliang |
| 武汉病毒研究 | Virology research in Wuhan |
| 武汉 AND 李医生 | Wuhan AND Dr. Li |
| 武汉 AND 疫情 | Wuhan AND Epidemic |
| 国家疾控中心 | Chinese Center for Disease Control and Prevention |
| 武汉 AND 疫苗 | Wuhan AND Vaccine |
| 管轶 | Guan Yi |
| 武汉 AND 征用宿舍 | Wuhan AND Requisitioned students' dormitory |
| 周佩仪 | Zhou Peiyi |
| 武汉中心医院 | The Central Hospital of Wuhan |
| 张晋 AND 卫健委 | Zhang Jin AND Health Commission |
| 张晋 AND 卫生健康委员会 | Zhang Jin AND Health Commission |
| 刘英姿 AND 卫健委 | Liu Yingzi AND Health Commission |
| 刘英姿 AND 卫生健康委员会 | Liu Yingzi AND Health Commission |
| 王贺胜 AND 卫健委 | Wang Hesheng AND Health Commission |
| 王贺胜 AND 卫生健康委员会 | Wang Hesheng AND Health Commission |
| 企业复工 | Enterprise work resuming |
| 中小企业 AND 困境 | Small and medium-sized enterprise AND Dilemma |
| 超市采购 | Supermarket Purchase |
| 地区       | 名称     |
|------------|----------|
| 西贝       | Xibei    |
| 武汉 AND 死亡病例 | Wuhan AND Death cases |
| 武汉 AND 感染病例 | Wuhan AND Infection cases |
| 湖北 AND 死亡病例 | Hubei AND Death cases |
| 湖北 AND 感染病例 | Hubei AND Infection cases |
| 中国 AND 死亡病例 | China AND Death cases |
| 中国 AND 感染病例 | China AND Infection cases |
| 潜伏期     | Incubation period |
| 北京 AND 病例 | Beijing AND Cases |
| 天津 AND 病例 | Tianjin AND Cases |
| 河北 AND 病例 | Hebei AND Cases |
| 辽宁 AND 病例 | Liaoning AND Cases |
| 上海 AND 病例 | Shanghai AND Cases |
| 江苏 AND 病例 | Jiangsu AND Cases |
| 浙江 AND 病例 | Zhejiang AND Cases |
| 福建 AND 病例 | Fujian AND Cases |
| 山东 AND 病例 | Shandong AND Cases |
| 广东 AND 病例 | Guangdong AND Cases |
| 海南 AND 病例 | Hainan AND Cases |
| 山西 AND 病例 | Shanxi AND Cases |
| 内蒙古 AND 病例 | Inner Mongolia AND Cases |
| 吉林 AND 病例 | Jilin AND Cases |
| 黑龙江 AND 病例 | Heilongjiang AND Cases |
| 安徽 AND 病例 | Anhui AND Cases |
| 江西 AND 病例 | Jiangxi AND Cases |
| 河南 AND 病例 | Henan AND Cases |
| 湖北 AND 病例 | Hubei AND Cases |
| 湖南 AND 病例 | Hunan AND Cases |
| 广西 AND 病例 | Guangxi AND Cases |
| 四川 AND 病例 | Sichuan AND Cases |
| 贵州 AND 病例 | Guizhou AND Cases |
| 云南 AND 病例 | Yunnan AND Cases |
| 西藏 AND 病例 | Tibet AND Cases |
| 陕西 AND 病例 | Shanxi AND Cases |
| 甘肃 AND 病例 | Gansu AND Cases |
| 青海 AND 病例 | Qinghai AND Cases |
| 宁夏 AND 病例 | Ningxia AND Cases |
| 新疆 AND 病例 | Xinjiang AND Cases |
| 香港 AND 病例 | Hong Kong AND Cases |
| 澳门 AND 病例 | Macau AND Cases |
| 台湾 AND 病例 | Taiwan AND Cases |
| ECMO       | Extracorporeal Membrane Oxygenation |
| 人工肺     | Extracorporeal membrane oxygenation |
| 双盲测试   | Double blind test |
| 核酸检测   | Nucleic acid testing |
| 疫苗       | Vaccine |
| 小区出入证 | Community pass card |
| 战疫       | Anti-COVID-19 |
| 抗疫       | Anti-COVID-19 |
| 全国疫情   | Epidemic in China |
| 囤积口罩   | Hoarding mask |
| 湖北卫健委 AND 免职 | Health commission of Hubei Province AND Remove from the position |
| 发热患者   | Fever patients |
| 延迟开学   | Postpone the reopening of school |
| 开学时间 AND 不得早于 | The start time of school AND Not earlier than |
| 累计死亡数 | Cumulative deaths |
| 疑似病例   | Suspicious cases |
| 入户排查   | Household troubleshooting |
| 武汉市慈善总会 | Wuhan Charity Federation |
预防物资  Epidemic control and prevention materials
捐赠物资  Donation materials
俄罗斯 AND 捐赠  Russia AND Donations
巴基斯坦 AND 捐赠  Pakistan AND Donations
美国 AND 捐赠  United States AND Donations
日本 AND 捐赠  Japan AND Donations

MERS  Middle East Respiratory Syndrome
中央赴湖北指导小组  Delegation from central government to guide Hubei
抗击 AND 新型肺炎  Fight against AND COVID-19
支援武汉  Give a hand to Wuhan
医用口罩  Surgical mask
武汉 AND 新增  Wuhan AND Novel cases
临床确诊病例  Clinically diagnosed cases
应勇 AND 湖北  Ying Yong AND Hubei
应勇 AND 上海  Ying Yong AND Shanghai
蒋超良 AND 湖北  Jiang Chaoliang AND Hubei

C. Table S2: Extended metrics for evaluating the performance of classifiers constructed by machine learning for ingroup sick posts

| Model | F1-measure | Precision | Accuracy | Recall |
|-------|------------|-----------|----------|--------|
| Decision Tree | 0.835 | 0.840 | 0.830 | 0.830 |
| Extra Tree | 0.785 | 0.785 | 0.785 | 0.785 |
| Extra Trees | 0.878 | 0.881 | 0.885 | 0.885 |
| K-nearest Neighbors | 0.810 | 0.819 | 0.819 | 0.819 |
| Multi-layer Perceptron | 0.847 | 0.845 | 0.851 | 0.851 |
| Support Vector Machine | 0.877 | 0.877 | 0.878 | 0.878 |
| Random Forest | 0.880 | 0.885 | 0.888 | 0.888 |

D. Table S3: Summaries of daily difference of new case numbers regressed on daily differences of sick post numbers (N = 94)

$\Delta C_t$ denotes the difference of new case counts at day $t$ from day $t-1$, $\Delta S_t$ denotes difference of sick post numbers (normalized) at day $t$ from day $t-1$. Robust estimation was adopted on this model. Date range spans from November 20th, 2019 to March 3rd, 2020. The diagnostic criteria change was controlled, which represents as $I$.

|          | Model 1 (National) | Model 2 (Hubei) | Model 3 (Outside Hubei) |
|----------|--------------------|-----------------|------------------------|
| $\Delta C_t$ | $\Delta C_t$ | $\Delta C_t$ |
| Estimate (95% CI) | p value | Estimate (95% CI) | p value | Estimate (95% CI) | p value |
| Intercept | -143.510 (-235.727 to -51.293) | 0.003 | -102.416 (-219.459 to 14.627) | 0.085 | -0.498 (-9.374 to 8.378) | 0.911 |
| $I$ | 11012.590 (8919.618 to 13105.560) | <0.001 | 12648.680 (11960.920 to 13336.440) | <0.001 | -137.729 (-292.918 to 17.460) | 0.081 |
| Lag term of new cases | .. | .. | .. | .. | .. | .. |
| $\Delta C_{t-1}$ | -0.700 (-0.935 to -0.465) | <0.001 | -0.597 (-0.875 to -0.318) | <0.001 | -0.055 (-0.511 to 0.401) | 0.810 |
| $\Delta C_{t-2}$ | -0.615 (-0.910 to -0.319) | <0.001 | -0.502 (-0.811 to -0.192) | <0.002 | -0.085 (-0.313 to -0.142) | 0.457 |
| $\Delta C_{t-3}$ | -0.507 (-0.741 to -0.273) | <0.001 | -0.378 (-0.675 to -0.081) | 0.013 | 0.223 (+0.002 to 0.448) | 0.052 |
| $\Delta C_{t-4}$ | -0.376 (-0.568 to -0.184) | <0.001 | -0.269 (-0.537 to -0.002) | 0.048 | 0.076 (-0.279 to 0.431) | 0.672 |
| $\Delta C_{t-5}$ | -0.276 (-0.461 to -0.092) | 0.004 | -0.187 (-0.425 to 0.051) | 0.121 | 0.154 (-0.124 to 0.431) | 0.274 |
| $\Delta C_{t-6}$ | -0.163 (-0.328 to 0.003) | 0.055 | -0.113 (-0.315 to 0.089) | 0.268 | 0.221 (-0.107 to 0.549) | 0.184 |
| $\Delta C_{t-7}$ | -0.124 (-0.275 to 0.026) | 0.104 | -0.121 (-0.296 to 0.053) | 0.169 | -0.121 (-0.431 to 0.188) | 0.438 |
| $\Delta C_{t-8}$ | -0.053 (-0.161 to 0.054) | 0.327 | -0.086 (-0.244 to 0.072) | 0.280 | -0.189 (-0.446 to 0.068) | 0.147 |
| $\Delta C_{t-9}$ | -0.036 (-0.107 to 0.035) | 0.312 | -0.092 (-0.233 to 0.049) | 0.197 | -0.182 (-0.373 to 0.008) | 0.061 |
| $\Delta C_{t-10}$ | -0.028 (-0.087 to 0.031) | 0.350 | -0.042 (-0.167 to 0.083) | 0.505 | -0.234 (-0.496 to 0.028) | 0.079 |
| $\eta^2$ | 0.705 | .. | 0.665 | .. | 0.233 | .. |
Formula of this model: \( \Delta C_t = a_0 + \sum_{i=1}^{m} \alpha_i \Delta C_{t-i} + \sum_{j=1}^{m} b_j \Delta S_{t-i} + c_t \epsilon_t + \epsilon_t \)

E. Table S4: Summaries of daily difference of new case numbers regressed on daily differences of other Covid-19 post numbers (N=94)

\( \Delta C_t \) denotes the difference of new case counts at day t from day t-1, \( \Delta N_t \) denotes difference of other Covid-19 post numbers (normalized) at day t from day t-1. Robust estimation was adopted on this model. Date range spans from November 20th, 2019 to March 3rd, 2020. The diagnostic criteria change was controlled, which represents as I.

| Lag term of sick-post ratios | Model 4 (National) | Model 5 (Hubei) | Model 6 (Outside Hubei) |
|-----------------------------|--------------------|-----------------|------------------------|
| \( \Delta S_{t-1} \)        | -1.252 (-0.308 to 2.196) | 0.010 148.086 (-88.797 to 384.969) | 0.217 0.116 (-3.761 to 3.993) | 0.952 |
| \( \Delta S_{t-2} \)        | -1.528 (-0.327 to 2.729) | 0.013 298.502 (33.969 to 563.035) | 0.028 5.407 (2.033 to 8.781) | 0.002 |
| \( \Delta S_{t-3} \)        | 2.654 (1.390 to 3.917) | <0.001 420.024 (133.748 to 706.300) | 0.005 1.153 (-3.012 to 5.317) | 0.583 |
| \( \Delta S_{t-4} \)        | 2.320 (0.788 to 3.851) | 0.003 420.130 (151.758 to 690.501) | 0.003 5.713 (2.195 to 9.231) | 0.002 |
| \( \Delta S_{t-5} \)        | 2.739 (1.261 to 4.216) | <0.001 471.131 (173.432 to 768.829) | 0.002 3.402 (-2.448 to 9.252) | 0.250 |
| \( \Delta S_{t-6} \)        | 3.885 (2.227 to 5.543) | <0.001 357.521 (80.231 to 670.812) | 0.013 9.624 (2.595 to 16.654) | 0.008 |
| \( \Delta S_{t-7} \)        | 2.686 (-0.200 to 5.171) | 0.035 312.833 (14.971-16.695) | 0.040 1.556 (-3.238 to 6.350) | 0.520 |
| \( \Delta S_{t-8} \)        | 2.545 (-0.840 to 5.929) | 0.138 200.695 (-64.967 to 466.356) | 0.136 2.038 (-2.325 to 6.400) | 0.355 |
| \( \Delta S_{t-9} \)        | 1.193 (-1.234 to 3.621) | 0.330 63.208 (-195.346 to 356.725) | 0.619 -2.124 (-6.198 to 1.950) | 0.302 |
| \( \Delta S_{t-10} \)       | 0.906 (-0.627 to 2.439) | 0.242 92.737 (-116.868 to 302.343) | 0.381 -1.510 (-5.062 to 2.042) | 0.400 |
| \( \eta^2 \)                | 0.614                | -- 0.235 | -- 0.413 | -- |
| \( R^2 \)                   | 0.941                | -- 0.902 | -- 0.542 | -- |
Formula of this model: $\Delta C_t = a_0 + \sum_{i=1}^{m} a_i \Delta C_{t-i} + \sum_{j=1}^{m} b_j \Delta N_{t-i} + c_t I_t + \varepsilon_t$

F. Table S5: Vector autoregression results of daily difference of new case numbers and daily difference of sick post numbers (N=94)

$\Delta C_t$ denotes the difference of new case counts at day t from day t-1, $\Delta S_t$ denotes difference of sick post numbers (normalized) at day t from day t-1. Due to the small sample size, we adjusted the degree-of-freedom and adopted the small-sample t and F statistics to calculate the coefficients. Date range spans from November 20th, 2019 to March 3rd, 2020. The diagnostic criteria change was controlled, which represents as I.

| Model 7 (National) | $\Delta C_t$ | $\Delta S_t$ |
|--------------------|--------------|--------------|
|                    | Estimate (95% CI) | p value | Estimate (95% CI) | p value |
| Intercept          | -143.510 (-243.660 to -43.360) | 0.006 | 6.355 (-19.280 to 31.990) | 0.623 |
| 1                  | 11012.590 (9467.031 to 12558.150) | $<0.001$ | -467.544 (-863.153 to -71.935) | 0.021 |
| Lag term of new cases | $\Delta C_{t-1}$ | $-0.700 (-0.825 to -0.575)$ | $<0.001$ | $-0.016 (-0.048 to 0.016)$ | 0.334 |
|                    | $\Delta C_{t-2}$ | $-0.615 (-0.784 to -0.445)$ | $<0.001$ | $0.036 (+0.008 to 0.079)$ | 0.104 |
|                    | $\Delta C_{t-3}$ | $-0.507 (-0.681 to -0.333)$ | $<0.001$ | $0.036 (+0.008 to 0.081)$ | 0.111 |
|                    | $\Delta C_{t-4}$ | $-0.376 (-0.540 to -0.213)$ | $<0.001$ | $0.055 (0.013 to 0.097)$ | 0.010 |
|                    | $\Delta C_{t-5}$ | $-0.276 (-0.406 to -0.147)$ | $<0.001$ | $0.009 (-0.024 to 0.042)$ | 0.590 |
|                    | $\Delta C_{t-6}$ | $-0.163 (-0.294 to -0.031)$ | 0.016 | $0.009 (-0.025 to 0.042)$ | 0.613 |
|                    | $\Delta C_{t-7}$ | $-0.124 (-0.253 to 0.004)$ | 0.058 | $0.035 (0.003 to 0.068)$ | 0.035 |
|                    | $\Delta C_{t-8}$ | $-0.053 (-0.162 to 0.055)$ | 0.331 | $0.031 (0.003 to 0.058)$ | 0.031 |
|                    | $\Delta C_{t-9}$ | $-0.036 (-0.126 to 0.054)$ | 0.428 | $0.014 (-0.099 to 0.038)$ | 0.216 |
|                    | $\Delta C_{t-10}$ | $-0.028 (-0.101 to 0.045)$ | 0.449 | $-0.002 (-0.021 to 0.017)$ | 0.838 |
| $\eta^2$           | 0.705 | $<0.001$ | $0.259$ | $<0.001$ |
| Lag term of sick-post ratios | $\Delta S_{t-1}$ | 1.252 (0.397 to 2.106) | 0.005 | $-0.387 (-0.606 to -0.169)$ | 0.001 |
|                    | $\Delta S_{t-2}$ | 1.526 (0.670 to 2.386) | 0.001 | $-0.265 (-0.485 to -0.045)$ | 0.019 |
|                    | $\Delta S_{t-3}$ | 2.654 (1.784 to 3.523) | $<0.001$ | $0.047 (+0.175 to 0.270)$ | 0.672 |
|                    | $\Delta S_{t-4}$ | 2.320 (1.386 to 3.254) | $<0.001$ | $-0.108 (-0.347 to 0.131)$ | 0.372 |
|                    | $\Delta S_{t-5}$ | 2.739 (1.777 to 3.700) | $<0.001$ | $-0.081 (-0.327 to 0.165)$ | 0.513 |
|                    | $\Delta S_{t-6}$ | 3.885 (2.790 to 4.980) | $<0.001$ | $0.295 (0.015 to 0.576)$ | 0.039 |
|                    | $\Delta S_{t-7}$ | 2.686 (1.233 to 4.138) | $<0.001$ | $0.167 (+0.205 to 0.539)$ | 0.373 |
|                    | $\Delta S_{t-8}$ | 2.545 (0.786 to 4.303) | 0.005 | $-0.213 (+0.663 to 0.237)$ | 0.349 |
|                    | $\Delta S_{t-9}$ | 1.193 (-0.468 to 2.855) | 0.157 | $-0.460 (-0.885 to -0.034)$ | 0.035 |
|                    | $\Delta S_{t-10}$ | 0.906 (-0.488 to 2.301) | 0.199 | $-0.722 (-1.079 to -0.365)$ | $<0.001$ |
| $\eta^2$           | 0.614 | $<0.001$ | $0.360$ | $<0.001$ |
| $R^2$              | 0.942 | $<0.001$ | $0.418$ | $<0.001$ |

Formulas of this model:

$\Delta C_t = a_0 + \sum_{i=1}^{m} a_i \Delta C_{t-i} + \sum_{j=1}^{m} b_j \Delta S_{t-i} + c_t I_t + \varepsilon_t.$

$\Delta S_t = d_0 + \sum_{i=1}^{m} d_i \Delta C_{t-i} + \sum_{j=1}^{m} e_j \Delta S_{t-i} + f_t I_t + \gamma_t$

G. Table S6: Vector autoregression results of daily difference of new case numbers and daily difference of other Covid-19 post numbers (N = 94)

$\Delta C_t$ denotes the difference of new case counts at day t from day t-1, $\Delta N_t$ denotes difference of other Covid-19 post numbers (normalized) at day t from day t-1. Due to the small sample size, we adjusted the degree-of-freedom and adopted the small-sample t and F statistics to calculate the coefficients. Date range spans from November 20th, 2019 to March 3rd, 2020. The diagnostic criteria change was controlled, which represents as I.
|                |                |                |                |                |
|----------------|----------------|----------------|----------------|----------------|
| Intercept      | -154.360 (-297.011 to -11.709) | 0.035           | 16.622 (-546.941 to 580.186) | 0.953          |
| I              | 12458.510 (10678.330 to 14292.680) | <0.001          | 595.184 (-6543.338 to 7735.706) | 0.868          |
| Lag term of new cases | .. | .. | .. | .. |
| \( \Delta C_t \) | -0.518 (-0.641 to -0.394) | <0.001 | 0.177 (-0.309 to 0.664) | 0.470 |
| \( \Delta C_{t-1} \) | -0.482 (-0.605 to -0.358) | <0.001 | -0.223 (-0.713 to 0.266) | 0.366 |
| \( \Delta C_{t-2} \) | -0.350 (-0.486 to -0.215) | <0.001 | -0.117 (-0.651 to 0.418) | 0.665 |
| \( \Delta C_{t-3} \) | -0.256 (-0.393 to -0.119) | <0.001 | -0.185 (-0.727 to 0.358) | 0.499 |
| \( \Delta C_{t-4} \) | -0.152 (-0.289 to -0.016) | 0.029 | -0.074 (-0.613 to 0.464) | 0.784 |
| \( \Delta C_{t-5} \) | -0.062 (-0.198 to 0.075) | 0.369 | 0.103 (-0.436 to 0.642) | 0.704 |
| \( \Delta C_{t-6} \) | -0.075 (-0.209 to 0.060) | 0.272 | -0.125 (-0.657 to 0.406) | 0.639 |
| \( \Delta C_{t-7} \) | -0.054 (-0.163 to 0.095) | 0.601 | 0.003 (-0.507 to 0.513) | 0.991 |
| \( \Delta C_{t-8} \) | -0.045 (-0.184 to 0.073) | 0.449 | -0.024 (-0.492 to 0.444) | 0.918 |
| \( \Delta C_{t-9} \) | -0.025 (-0.124 to 0.074) | 0.612 | 0.061 (-0.330 to 0.452) | 0.756 |
| \( \eta^2 \) | 0.566 | .. | 0.060 | .. |
| Lag term of non-sick-post ratios | .. | .. | .. | .. |
| \( \Delta N_{t-1} \) | 0.025 (-0.032 to 0.082) | 0.387 | -0.148 (-0.374 to 0.079) | 0.198 |
| \( \Delta N_{t-2} \) | 0.049 (-0.009 to 0.107) | 0.096 | 0.042 (-0.188 to 0.271) | 0.718 |
| \( \Delta N_{t-3} \) | 0.029 (-0.029 to 0.087) | 0.316 | 0.112 (-0.117 to 0.341) | 0.332 |
| \( \Delta N_{t-4} \) | 0.038 (-0.021 to 0.097) | 0.206 | 0.019 (-0.215 to 0.252) | 0.873 |
| \( \Delta N_{t-5} \) | 0.052 (-0.007 to 0.112) | 0.082 | 0.049 (-0.185 to 0.284) | 0.676 |
| \( \Delta N_{t-6} \) | 0.053 (-0.006 to 0.113) | 0.078 | -0.068 (-0.302 to 0.167) | 0.567 |
| \( \Delta N_{t-7} \) | 0.031 (-0.030 to 0.092) | 0.310 | -0.022 (-0.263 to 0.218) | 0.855 |
| \( \Delta N_{t-8} \) | 0.040 (-0.023 to 0.103) | 0.207 | -0.159 (-0.408 to 0.089) | 0.205 |
| \( \Delta N_{t-9} \) | 0.082 (-0.074 to 0.078) | 0.950 | -0.062 (-0.363 to 0.238) | 0.681 |
| \( \Delta N_{t-10} \) | 0.089 (0.026 to 0.173) | 0.099 | 0.368 (0.077 to 0.658) | 0.914 |
| \( \eta^2 \) | 0.244 | .. | 0.161 | .. |
| \( R^2 \) | 0.883 | .. | 0.186 | .. |

Formulas of this model:

\[ \Delta C_t = a_0 + \sum_{i=1}^{m} a_i \Delta C_{t-i} + \sum_{j=1}^{m} b_j \Delta N_{t-i} + c_1 l_t + \varepsilon_t, \]

\[ \Delta N_t = d_0 + \sum_{i=1}^{m} d_i \Delta C_{t-i} + \sum_{j=1}^{m} e_j \Delta N_{t-i} + f_1 l_t + \gamma_t. \]