

Statistical procedures for evaluating trends in coronavirus disease-19 cases in the United States

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ABSTRACT

Objectives: In late 2019, a novel respiratory disease was identified as it began to spread rapidly within China's Hubei Province soon thereafter, being designated coronavirus disease 2019 (COVID-19). Unfortunately, trends in cases and rates of infection have been consistently misunderstood, particularly within the media, due to little, if any, statistical analysis of trends. Critical analysis of data is necessary to determine how to best manage local restrictions, particularly if there are resurgences of infection. As such, researchers have been calling for data-driven, statistical analysis of trends of disease to provide more context and validity for significant policy decisions.

Methods: This quantitative study sought to explore different statistical methods that can be used to evaluate trend data to improve decision-making and public information on the spread of COVID-19. Analyses were conducted using Spearman's rho, Mann-Whitney *U* tests, Mann-Kendal tests, and Augmented Dickey-Fuller tests with follow up Kwiatkowski-Phillips-Schmidt-Shin tests.

Results: The results indicated a mix of both surprising and expected findings. Variations among COVID case reporting for each day of the week were identified but not deemed significant. Spearman correlation data appeared to perform well in identifying monotonic trend while Mann-Kendal tests appeared to provide the most intelligible results.

Conclusions: This study provides examples of statistical tools and procedures to more thoroughly examine trends in COVID-19 case rate data. It is advocated that such metrics be made available to health and policy stakeholders for potential use for public health decisions.

Keywords: Coronavirus disease 2019, trends, statistics, public health, U.S

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Introduction

In late 2019, an infection of unknown origin with respiratory disease manifestations was identified as it began to spread rapidly within China's Hubei Province, in particular within its largest city, Wuhan. Soon thereafter, the World Health Organization termed to the illness coronavirus disease 2019 (COVID-19).^[1] By January 30, 2020, the rapid spread of this new disease across the globe became evident, leading to the WHO declaring COVID-19 a Public Health Emergency of Concern and by March, the outbreak was designated a "pandemic."^[2,3] As of the beginning of June 2020, the total number of COVID-19 cases across the globe topped 7.3 million and the total deaths reached 414,000. In the U.S. alone, the cases had nearly reached 2 million and the number of deaths had almost hit 113,000.^[4] Although many locations, particularly those countries and states hardest hit by the disease, have seen dramatic decreases in the numbers of new cases and deaths,

there are many more locations in which the trends in infections and deaths are unclear or, worse, increasing.^[1,3] Of particular concern in the resurgence of COVID-19 infections in light of relaxing of rules by local governments designed to prevent the spread of the disease such as quarantine, business closures, and social distancing.^[5,6] Further exacerbating the potential of a resurgence of infection is the waves of public protests that have been occurring in many countries across the globe in response to police brutality in the United States.^[7]

The problem is that "the trends of daily incidence and deaths of COVID-19 in the USA are still poorly understood,"^[8] in particular, sources of data provide little, if any, statistical analysis of trends. As the U.S. begins to reopen following COVID-19 restrictions, it is critical for governments, businesses, and the general public means for scrutinizing changes in cases and deaths to determine relevant trends in the data. Just as importantly, critical analysis of data is necessary

to determine if restrictions should be reimplemented in light of a substantial trend in resurgence. As such, researchers have been calling for data-driven, statistical analysis of trends of disease to provide more context and validity for significant policy decisions such as reopening or restricting economic activities, ordering and staging of medical equipment, and travel limitations.^[1,3,8-10] Rapid response to data trends has been credited for reducing the spread of COVID-19 in countries such as China, South Korea, and Singapore, further indicating the importance of data quality and the analysis of such data.^[1] This study sought to explore different statistical methods that can be used to evaluate trend data to improve decision making and public information on the spread of COVID-19. Examples of the implementation of these methods on recent COVID-19 new case counts and incidence rates in the U.S. are provided.

A new threat: COVID-19

Emerging from Wuhan, China, in late 2019, COVID-19 is the third coronavirus epidemic to occur in the last two decades. It is surmised that the virus originated through zoonotic transmission from an animal being sold in a “wet” market in Wuhan. This carrier animal most likely picked up the virus from bat guano when foraging in proximity to local caves.^[3] It became quickly apparent that Wuhan was experiencing a strange, new pneumonia-like disease, as cases began to crop up in local hospitals. Symptoms included fever, malaise, and cough. It was determined soon after the discovery that the primary means of COVID-19 transmission were through respiratory droplet expulsion and inhalation. Of particular concern was the seemingly rapid transmission among the local population and soon beyond.^[1] Preliminary estimates of viral reproduction numbers have ranged from 1.4 to 3.8 in comparison to H1N1 (1.25) and Severe Acute Respiratory Syndrome (2.2–3.6).^[3] Estimates of mortality ratios among COVID-19 patients vary based upon the location of the victim, ranging from 15.3% in France to 1.3% in Russia. The mortality ratio in the U.S. as of June 2020 was 5.7%.^[4] Part of the local variances in mortality is likely tied to large numbers of individuals that have demographic features related to a higher incidence of fatalities such as being over the age of 80, the existence of comorbidities (such as diabetes), and those with compromised immunities.^[1,8]

Trends in COVID-19 data

Researchers and governments from around the globe immediately started to monitor trends in COVID-19 data to ascertain the speed and scope of the spread of the virus. Complicating these efforts, trends in COVID-19 cases and deaths have been in constant flux since the disease was identified and actively tracked.^[3] While disease activity rapidly rose in one location, it may only rise slowly in others while in some locales, the has been minimal spread. Furthermore, as one region or country may experience increases in incidence, others simultaneously appear to have passed the peak number of cases and deaths, with infections apparently in decline. For example, confirmed cases in China peaked in mid-February

2020, cases in Italy did not reach maximum values until around March 21, cases (as of early June 2020) in Brazil are still rising, and in the U.S., cases reached a highpoint toward the end of April 2020. However, there appears to be a potential for resurgence manifesting in individual states. In general, global cases and deaths have continued to climb at an alarming pace.^[3,4]

Due to the rapid spread and deadly nature of COVID-19, countries have implemented a variety of levels of preventative mechanisms and guidance at various speeds or stages, to contain the spread of the virus. China’s rapid lockdown has been credited with curtailing viral spread to a higher number than have been experienced.^[3] Furthermore, social distancing and quarantine measures appear to have had significant positive impacts on transmission in Italy. Further, similar policies in the U.S. initially showed a “flattening of the curve” of infection in most states. Such efforts also are credited to finally interrupting the rapid outbreak in the New York City area.^[11-13]

While there has been a significant amount of forecast modeling and research, there is little data available on the active monitoring of current data trends and both their statistical and practical significance.^[8,14-17] At present, short-term trends are commonly described by changes in the numbers and percentages in cases which, when used in isolation of other metrics, can be misleading.^[18,19] In particular, there appears to be a strong relationship between the number of reported cases and the day of the week, most likely due to the way that tests and other data are collected and disseminated. Thus, a 1- or 2-day jump in cases must be taken in the context of these patterns. In response to concerns on using these simple measures, media and researchers have opted for the use of various moving average metrics such as simple moving/rolling averages, which include 3, 5, or 7-day periods. While these improved means of visualizing data trends are helpful, they do not provide magnitude and significance of variations.^[20,21] The quality of trend data has been identified as critical to the decision making on both restrictions and lifting thereof, with subsequent monitoring of such trends being viewed as critical to avoiding the rapid reinfection of the public.^[22-24]

Unfortunately, the media and even some government agencies report trends based upon daily changes in cases and deaths, which is not only misleading but potentially erroneously naming temporary fluctuations as new tendencies.^[1,8,14,17] This creates confusion among the public and other stakeholders, leading to changes in behavior that may put their health at risk (e.g., discontinuing the use of a mask, venturing out more often, and socializing in large groups).^[6,8,14-17]

Measuring and significance of trends

There is a wide range of statistical methods for quantifying both trends and their significance within the literature. Moreover, there have been exploratory studies explicitly on COVID-19 that outline possible options for trend analysis.

Pearson correlation was used to examine the relationship between new cases of COVID-19 with Google searches on the virus over time.^[8] The authors measured correlations at various days of lag between the search counts and the new case metric to account for incubation periods. There was no significant correlation found between cases and searches at day 7 ($P = 0.178$) but highly significant, strong correlations at days 12 ($r = 0.978, P \leq 0.001$) and nineteen ($r = 0.973, P \leq 0.001$). Spearman correlation trend tests were employed to evaluate the relationship between acute infection incidence and year with findings showing significant differences between incidence in 2004 and 2014 ($P < 0.001$).^[24] The use of Spearman's correlation has also been advocated in order to determine monotonic trends over time, particularly in exploratory studies.^[25] Extending this type of use of Spearman correlation, it was determined that one could robustly compare two Spearman's rho values, much like Pearson values utilizing Fisher's z -transformation. Researchers found, through Monte Carlo simulations, treating Spearman as Pearson values were more capable of avoiding Type I errors than alternatives such as ignoring normality assumptions.^[26]

While there is some consensus that Spearman correlation is a suitable statistical test for trends in time series, some literature has also mentioned that specific applications may benefit from the use of Mann-Kendall (M-K) tests.^[27] M-K tests assume an H_0 of near-identical or identical distributions of datasets versus a H_a of the existence of a monotonic trend.^[27-29] If there are concerns about "seasonality" effects on trends, an extension of the M-K test, the Seasonal Kendall (S-K) test can be used.^[30] The term seasonality is not limited to calendar seasons (e.g., spring, summer). It can refer to any period where variation may regularly occur, such as days, months, and quarters. For the S-K test, the H_0 of there is no monotonic trend versus a H_a of for one or more of the "seasons," there is the existence of a monotonic trend.^[31]

Two additional analyses to detect trends have been recently used in studies about cases and prevalence of COVID-19. Dickey-Fuller (D-F) tests have been used to determine the trend in daily effective reproductive numbers (R).^[3] An improvement on the D-F, the Augmented DF (ADF) test, has also been described in the time series analysis literature. It can handle more complex data.^[32] The ADF test purports an H_0 of non-stationarity of data versus a H_a of stationarity data, that is, variance and mean do not vary over time. In short, these tests seek to determine stationarity and the potential source of variations, such as seasonality or an actual trend.^[33] Finally, the utility of Mann-Whitney U tests in evaluate time-series data utilizing the Monte Carlo method has also been described in recent literature. This technique allowed for the identification of non-overlapping time segments.^[34]

Methods

To explore the utility of the described statistical procedures for analyzing trends in COVID-19 data, daily rates of cases per 100,000 individuals were collected for the U.S. as well as several individual states. The states were selected based upon

their COVID-19 incidence history or recent reports of "surges" in cases. New York was selected because it appears that the state has passed peak infection and would provide meaningful insight into the utility of trends in retrospection. Georgia was selected due to its seemingly stable numbers of cases in May and June. Two states with reported surges in cases in June 2020, Arizona, and Texas were also included. Finally, the state of Louisiana appeared to have a possible definite uptick in cases in June as well, though the data were not yet conclusive.

Sampling procedures

The new rates by day for the U.S. were mined from the Center for Disease Control (CDC) COVID Data Tracker website.^[35] The case and rate (if available) values for individual states were collected from the individual state health data repositories through the COVID Tracking Project, which receives data feeds from state health data providers several times per day.^[36] For states that did not provide the rates of infection, these were calculated using the same data and formula used by the CDC's COVID Data Tracker. The data were saved in excel to be analyzed with both SPSS and XLSTAT software.

Research design

This exploratory study sought to identify statistical means for better understanding daily rate trends in COVID-19 data. Due to the expected cyclical nature of data reporting by day of the week, variations in reporting for each day of the week were evaluated. This was deemed necessary to fairly evaluate trends or changes to capture a full data trend period rather than looking at only the most recent day or days of data. Thus, the minimum "recent" period for trend analysis used was determined from this initial analysis. To evaluate the efficacy of different trend analysis procedures, the data as mentioned earlier was assessed using Spearman correlation trend tests, Spearman's rho comparisons through Fisher's z -transformation, M-K tests, ADF tests (with follow up Kwiatkowski-Phillips-Schmidt-Shin [KPSS] tests for time trends), and Mann-Whitney U tests (Monte Carlo method). Tests were selected based upon the guidance from XLSTAT (2019) as well as previous research.^[3,8,24,37] Pearson correlation was opted to be omitted due to potential violations of assumptions. Except for New York State, data were limited to the period from April 1 through June 10 and were used to ensure consistency across groups. In the instance of New York State, trend data were compared to subsequent data to see if identified trends had any predictive value.^[3,8,24]

Results

The performance of each test is outlined below. Initial screening of the data was conducted using a Kruskal-Wallis test to determine variation in counts for each day of the week. While there appeared to be higher counts noted from all data sources for the periods of Thursday through Saturday, none were found to be significant. Mann-Whitney U tests were then

conducted to determine if the difference between the Sunday through Wednesday and the Thursday through Saturday periods were significant. The P values for each data set are shown in Table 1 (See Appendix for all Tables).

Spearman correlations were conducted for each geographical area starting on June 10, 2020, and then moving backward 5, 7, and 14 days. The resultant rho values are outlined in Table 2.

Comparisons of Spearman's rho values were then calculated using utilizing Fisher's z -transformations. The resultant P values for each geographical area were determined for the pairs of days ranging from the last five to the last fourteen. Table 3 shows the breakdown of these tests.

Mann-Whitney U tests were conducted to compare the period of May 21 through June 3 (14 days) versus the most recent 7 days, from June 4 through 10. The U value and trend directions, if applicable, are outlined in Table 4.

Since New York state appeared to be the first in the U.S. to good through an entire trend period (i.e., large increase, peak, then large decrease in cases), a wider range of dates was used to evaluate Spearman correlations and comparisons. Tables 5 and 6 for the outputs from these tests.

The results of M-K and ADF (with KPSS) tests for each state are shown in Tables 7-16. Tests use a start date of June 10, 2020, and then moved backward 5, 7, and 14 days

Finally, it should be noted that Bonferroni corrections were omitted due to the exploratory nature of this study, per recommendations of existing research.^[38] *Post hoc* application of such corrections can be made by those interested.

Discussion

The results indicated a mix of both surprising and expected findings. Initially, it was assumed that there would be a significant difference among case counts for certain days of the week (due to the visual presentations of cases) which would have significance for the types of methods used for reporting, for example, moving averages needing to include a full case count cycle, as well as statistical evaluation of such data. However, the lack of significance of Kruskal-Wallis results indicated these patterns were not as pronounced as expected. Nevertheless, there did appear to be clear patterns in data reporting with regularly higher values occurring from Thursday through Saturday in most locations. This, of course, can be hypothesized to be a function of lags in reporting or other administrative issues, not the actual increase in the incidence of cases on those days. To examine these patterns further, data from Sunday through Wednesday were compared to that of Thursday through Saturday. None of the tests showed significant differences, although Arizona, Texas, and Louisiana data ($0.05 < P < 0.10$) raises some

possible concerns about the need factor into account the day of the week when examining case data.^[39]

Spearman correlation data shed light on the general monotonic trend in data, which can reinforce purported trends in rates of cases. While some argue that significance in correlation data is irrelevant, the significance of 2-week declines of rates of cases in New York, for example, aligns with a period of downward trending case numbers.^[40] Examining the rho values more closely, one could argue that concerns would be in order if there were identifiable positive trends from the past 2 weeks toward more recent data. For example, the U.S. data went from slightly negative to significantly and strongly positive, which could potentially be a warning sign. Georgia, on the other hand, appears to go from positive to relatively level, a sign that could be of less concern.

When comparing rho values, more details emerge from the data. For the U.S., the change in Spearman's rho from 2 weeks before the most recent 5 days was found to be highly significant. This appears to reinforce the original Spearman findings. Similarly, in New York, the criticality of a trend changing from a significant, strong negative correlation to a positive, albeit non-significant value, is noted by the change being determined also to be significant. While these were the only two comparisons with significant results, one can again invoke the arguments made by some researchers that, particularly in explorations of data, that significance should be viewed as being more fluid rather than dichotomous, with levels near values of significance worthy of the attention of stakeholders.^[39] As such, comparisons of days 5–7 for both the U.S. and New York could indicate trends worth flagging for further monitoring.

When examining the periods of May 21 through June 3, 2020, versus June 4 through 10, 2020, utilizing Mann-Whitney U tests, both New York and Arizona showed significant differences. However, the trends were the opposite, down for New York and up for Arizona. Texas also showed an upward trend, though only significant at $P < 0.10$.

More concrete trends could be seen among the expanded explorations of Spearman correlations and comparisons for New York. Strong and significant correlations were indicated for known periods of large changes in rates of cases. The data in Table 5 present a valid argument for the alignment of data trends with significant rho values. The Spearman data also clearly shows the transition from rate increases to peak value to decreases. The comparisons among Spearman values appeared to reinforce the findings in Table 5. Further, the comparison test results logically followed trends in rho values across timeframes.

Looking at Table 7, along with the opposite New York data in Table 2, it can be seen that the findings align both in significance and direction of trends. Sen's slopes can help provide insights into the magnitude of a time series trend and can be especially discriminating as it is robust even in light of outliers.^[41] The

details in Table 8 seem to echo the downward trends in New York shown in Tables 2 and 7, adding some details about the variation in cases, namely more stability in the most recent 5 days.

Data for Arizona in Tables 9 appear to follow a similar pattern as in Table 2 while the ADF and KPSS results in Table 10 agree with those for the Arizona Mann-Whitney U in Table 4. Like much of the data analyzed by the ADF, Arizona numbers were non-stationary, which was not unexpected based upon the wide ranges of cases seen for each day of the week. Examining the findings on Texas [Tables 2-4, 11, and 12], they appear to follow similar patterns as exhibited in Arizona. The only series of tests that did not indicate a case trend was the ADF/KPSS values.

Louisiana data performed as expected, although all tests other than the ADF/KPSS series showed a migration toward a positive uptick. Louisiana could serve as an example of a developing trend as rho and tau values incrementally increased in a more recent day ranges along with increases in Sen's slopes and reductions in P values for M-K tests. When the majority of tests agree, as exemplified by the New York state data, one can have increased confidence in the veracity of trend. Similarly, Georgia followed relatively stable patterns over the long term with migration toward upward movement in more recent days. Similar conclusions, as deduced from Louisiana data, are advocated for Georgia as well.

Based on the collective findings outlined in this study, a matrix of likely trends and suggested measures for stakeholders are presented in Table 17.

Conclusions

As highlighted in the literature, the understanding and analysis of trends in COVID-19 were deemed in need of further investigation. Due to the importance of meaningful conclusions based on trend data in making policy decisions for governments, businesses, and individuals, this study sought to provide a more in-depth examination of available data. While news headlines have regularly presented "surges" in cases, these findings often do not provide the perspective necessary to understand their meaning in light of larger-scale trend data. Further, daily reporting of case counts can be misleading, as shown in this study, namely that the average number of reported cases varies based upon the day of the week. Therefore, it is advocated here that moving or simple averages of periods that would capture an entire weekly data cycle be used to gauge the existence or development of a trend. For example, a minimum of 5–7 days of data would be needed to identify more stable trend information best.

While it would be helpful to identify one particular test or analysis to determine COVID-19 data trend characteristics, the findings of this study support the use of a range of measures to garner potential changes in and magnitude of a trend. From the expanded and basic New York state data, it can be seen that Spearman's rho, as well as M-K data, tended to accurately identify "obvious" data trends that were previously

known. Further verification came from Spearman correlation comparisons as well as the Mann-Whitney U test of recent versus past values. While ADF/KPSS results over more extended periods do appear to describe trends in rates of cases adequately, the findings are less intuitive than those of other tests. Moreover, the longer the term, the less utility a finding provides, as the conclusion of an upward or downward trend is usually intuitively determinable by such a point.

In summary, this study has provided examples of statistical tools and procedures to more thoroughly examine trends in COVID-19 case rate data. Similar methods could be extended to other indicators such as mortality rates and the numbers of tests administered. It is advocated that such metrics be made available to health and policy stakeholders for potential use for public health decisions.

Based on the findings of this study, the following recommendations for future research are presented:

1. Use of the presented statistical tests and procedures to conduct a follow-on study of data to determine the validity of the identified trend.
2. Further examination of other statistical tools and procedures that can be used to provide more short-term trend information.
3. Explore means for identifying the impact of increased testing on the counts and rates of COVID-19 infections.

Authors' Declaration Statements

Ethics approval and consent to participate

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Availability of data and material

All data used is publicly available online.

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Appendix

Table 1: Mann-Whitney U (Sun-Wed vs. Thu-Sat)

Location	<i>P</i>
U.S.	0.117
New York	0.312
Arizona	0.095
Texas	0.080
Louisiana	0.062
Georgia	0.944

Table 2: Spearman's rho: End date June 10, 2020

Location	Last 14 days	Last 7 days	Last 5 days
U.S.	-0.073	0.357	1.000*
New York	-0.789*	-0.250	0.600
Arizona	0.525	0.500	0.800
Texas	0.380	0.464	0.700
Louisiana	0.143	0.321	0.400
Georgia	0.405	0.321	0.900

(*significant $P < 0.05$)

Table 3: *P* values of spearman comparisons

Location	Last 7 versus 14 days	Last 5 versus 14 days	Last 5 versus 7 days
US	0.429	0.005*	0.051
New York	0.303	0.004*	0.070
Arizona	0.952	0.503	0.528
Texas	0.857	0.542	0.674
Louisiana	0.749	0.718	0.920
Georgia	0.865	0.173	0.186

(*significant $P < 0.05$)

Table 4: Mann-Whitney U: May 21–June 3 versus June 4–10

Location	<i>U</i>	Trend
U.S.	47	NA
New York	5*	Down
Arizona	83*	Up
Texas	72 ⁿ	Up
Louisiana	63	NA
Georgia	60.5	NA

(*significant $P < 0.05$; ⁿ $P = 0.05-0.10$)

Table 5: Expanded New York Spearman's rho

End dates	Past 14 days	Past 7 days	Past 5 days
16 March 20	0.761*	0.829*	0.821
23 March 20	0.975*	0.964*	1.000*
30 March 20	0.934*	0.679	0.100
07 April 20	0.736*	-0.071	-0.800
14 April 20	-0.275	-0.857*	-0.900 ⁿ
21 April 20	-0.767*	-1.000*	-1.000*
28 April 20	-0.556*	-0.500	-0.900 ⁿ
05 May 20	-0.807*	-0.821*	-0.900 ⁿ

(*significant $P < 0.05$; ⁿ $P = 0.05-0.10$)

Table 6: Expanded New York Capitalize Spearman comparisons

End dates	Last 7 versus 14 days	Last 5 versus 14 days	Last 5 versus 7 days
16 March 20	0.749	0.833	0.976
23 March 20	0.749	0.035*	0.038*
30 March 20	0.138	0.038*	0.401
07 April 20	0.083 ^a	0.008*	0.234
14 April 20	0.007*	0.121	0.825
21 April 20	<0.001*	<0.001*	NA
28 April 20	0.896	0.271	0.285
05 May 20	0.944	0.645	0.718

(*significant $P < 0.05$; ^a $P = 0.05 - 0.10$)**Table 7:** New York State M-K

Series\Test	Kendall's tau	P-value	Sen's slope
Last 5 days	0.400	0.483	28.250
Last 7 days	-0.238	0.562	-14.000
Last 14* days	-0.560	0.005	-44.571

Table 8: New York ADF and KPSS test results

Series\Test	ADF trend	KPSS trend
Last 5 days	Stationary*	None
Last 7 days	Non-stationary	None
Last 14 days	Non-stationary	Down*

(*significant $P < 0.05$)**Table 9:** Arizona M-K

Series\Test	Kendall's tau	P-value	Sen's slope
Last 5 days	0.600	0.233	229.125
Last 7 days	0.333	0.381	58.600
Last 14 days	0.363	0.079	62.200

Table 10: Arizona ADF and KPSS test results

Series\Test	ADF trend	KPSS trend
Last 5 days	Non-stationary	None
Last 7 days	Non-stationary	None
Last 14 days	Non-stationary	Up*

(* significant $P < 0.05$)**Table 11:** Texas M-K

Series\Test	Kendall's tau	P-value	Sen's slope
Last 5 days	0.600	0.233	317.875
Last 7 days	0.333	0.381	106.000
Last 14 days	0.253	0.233	40.900

Table 12: Texas ADF and KPSS test results

Series\Test	ADF trend	KPSS trend
Last 5 days	Stationary*	None
Last 7 days	Non-stationary	None
Last 14 days	Non-stationary	None

(*significant $P < 0.05$)

Table 13: Louisiana M-K

Series\Test	Kendall's tau	P-value	Sen's slope
Last 5 days	0.400	0.483	60.917
Last 7 days	0.238	0.562	24.000
Last 14 days	0.121	0.591	2.500

Table 14: Louisiana ADF and KPSS test results

Series\Test	ADF trend	KPSS trend
Last 5 days	Stationary*	None
Last 7 days	Non-stationary	None
Last 14 days	Non-stationary	None

(*significant $P < 0.05$)**Table 15:** Georgia M-K

Series\Test	Kendall's tau	P-value	Sen's slope
Last 5 days	0.800	0.083	91.250
Last 7 days	0.238	0.562	21.333
Last 14 days	0.309	0.125	10.917

Table 16: Georgia ADF and KPSS test results

Series\Test	ADF trend	KPSS trend
Last 5 days	Stationary*	None
Last 7 days	Non-stationary	None
Last 14 days	Non-stationary	None

(*significant $P < 0.05$)**Table 17:** Summary and recommendations matrix

Location	Trend	Recommendation*
U.S.	Up	Warning
New York	Stable/Down	Diligence
Arizona	Up	Warning
Texas	Up	Warning
Louisiana	Stable/Up	Caution
Georgia	Stable/Up	Caution

*Possible recommendations from most to least severe: Warning, caution, diligence, none