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# Potential Causes Related to Stock Market Volatility During COVID-19: Insights into the Performances in the US

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**Abstract:** The research aims to figure out the significant factors causing the volatility moves in the period from Feb 10 to Dec 28, 2020, which covers the outbreak and duration of COVID-19 in 2020, among the candidates: number of reports (cases, deaths, tests, and infection rate), number of medical resources needed (all beds needed, ICU beds needed, and invasive ventilators needed), and people's anticipation toward reality (stock market, the pandemic, state of the economic and personal finance). After performing OLS regressions with stepwise regressions forward further, whose independent variables are chosen based on the values of VIF, we conclude that people's focus on coronavirus is the most significant factor that induces the volatility, and the VIX values evolve dynamically. Nevertheless, the conclusions are somehow not robust as expected: in the second half of the period, not only none of the candidates are shown to have any influence on the volatility, but also the VIX series is proved to be not autocorrelated. By the results of the study, it is important not only to control the further spread of the pandemic but also to find approaches to stabilize people's emotions towards the aspects of life which are affected by the pandemic. Apart from the meaningful insights from the research, the research paves the way for further studies in the future.

**Keywords:** COVID-19; Volatility; Regression Analysis; Time Series Analysis; Variance Inflation Factor; Stepwise Regression; Google Trend; VIX; People's Focus on COVID-19; Autocorrelation

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## 1. Introduction

The frustrating pandemic, COVID-19, has made an irreversible and longstanding impact on people's daily life. Along with the pandemic, more lockdowns are in progress as the outbreak of confirmed cases continues, while medical resources in the US are on the verge of collapse. Meanwhile, people, including the investors, are suffering from mental instability, which stems from the isolation and the decline of personal finance. For the stock market, the stock price reactions suggest that broad actions, including fiscal policy interventions, are required to avoid further negative outcomes and propagations of the COVID-19 shock (Wagner <sup>[1]</sup>, 2020). Besides, people always mention volatility when trying to observe how significant an asset's prices swing around the mean price, and it is a statistical measure of its dispersion of returns. Therefore, it is important to observe how the volatility works during the pandemic.

Previous researches focus on the reported cases and deaths (Devpura and Narayan <sup>[2]</sup>, 2020; Baek et al. <sup>[3]</sup>, 2020; Albulescu <sup>[4]</sup>, 2020), and in a nutshell, the reported cases and deaths do have an impact on the financial volatility in the US. However, it may be a little too narrow if they are the only significant factors considered for the volatilities, which is claimed by Baker et al. <sup>[5]</sup> (2020) with more convincing evidences.

We may not consider the influence from media coverage by far: In the further explanation based on the comparison between COVID-19 and former remarkable pandemics, Baker et al. <sup>[5]</sup> (2020) claim that "the greater information availability and its more rapid diffusion to market participants cannot rationalize the huge stock market reaction to COVID-19" (p. 10), although they surely contributed to the performances. Coincidentally, in a study given by Haroon and Rizvi <sup>[6]</sup> (2020) later on, it is observed that "media coverage had little to moderate association with the volatility of prices" (p. 5).

As a conclusion of the study by Baker et al. <sup>[5]</sup> (2020), the researchers agree that the government restrictions on individual mobility and commercial activity, as well as voluntary social distancing, are the more promising factors causing the unprecedented market moves. However, Albulescu <sup>[7]</sup> (2020) additionally observes that the effect of EPU (Economic Policy Uncertainty Index, a measure of policy-related economic uncertainty) is insignificant to the volatility, and it is conjectured that “the COVID-19 uncertainty dominates the policy-induced uncertainty” (p.4) in the research. Governments’ intervention may be a factor that partially affects the volatility, while it is probably not a significant one.

Recall the study given by Haroon and Rizvi <sup>[6]</sup> (2020): the authors find that instead of news coverage, as well as the sentiments. Moreover, the study by Stephanos et al.<sup>[8]</sup> (2020), which is inspired by research on the sentiments and asset prices (Da, et al.<sup>[9]</sup> 2015) and based on Google’s search data, concludes with “a causal positive direct relationship between Google trend metrics for COVID-19 and stock market implied volatility” (p. 17).

In summary, people’s sentiments towards the pandemic, a more general topic involved with the government’s intervention are verified to be a more promising factor causing the heightening market moves during COVID-19.

On the one hand, most of the researches involved with the causes of the volatilities during the pandemic are merely based on the data in the first months, and for the pandemic to persist, the conclusions may be to be updated as time evolves. On the other hand, the conclusions for the reasons for the extraordinary stock market reaction to COVID-19 are still painted with a broad brush (Baker et al. <sup>[5]</sup>, 2020). Based on these facts, the study aims at investigating the potential causes and the corresponding effects to the volatility of stocks, plus focuses on data for ‘most’ of the year 2020, when the pandemic outbreaks and persists, instead of the very first months after the outbreak. The potential factors to be researched including:

- a) the number of reports of COVID-19
- b) the number of medical resources needed
- c) public anticipation towards the pandemic and the involved sectors, including personal finance, stocks, and lifestyle

## 2. Methodology

### (1) Data

The potential dependent variables sample covers three sectors, each of which includes several terms to be considered in the regression model:

- 1) The reports for the pandemic (denoted as **N**):  
Number of new cases, accumulated cases, new deaths, accumulated deaths, new tests, accumulating tests, infection rate (dividing the new cases number by the new tests number).
- 2) The medical resources needed (denoted as **M**):  
Number of all beds needed, all ICU beds needed, invasive ventilators needed.
- 3) Google Trends data (denoted as **G**):  
Searched terms: DJIA, S&P 500, Nasdaq, NYSE, VIX, GDP, CPI, Recession, Mortgage, Forbearance, Debt, Unemployment Benefits, Food Stamps, Food Bank, Stimulus.  
Thematic Terms: Coronavirus, Stock Market, Unemployment, Vaccine.

Note that, for public anticipation towards COVID-19, the Google Trend database is considered, as the trend value reflects the people’s interest in the searched item, and the increase Google trend implicitly represents people’s negative mood towards the pandemic (Sharma & Sharma <sup>[10]</sup>, 2020).

The data for session N is distributed by databases of *WHO* and *IHME*<sup>1</sup>. The data for session M is distributed by the database of *IHME*. Finally, the G session data is distributed by the *Google Trends*<sup>2</sup>, which provides the search terms in each sub-topic: state of the economy, personal finances, employment, and relief.

Eventually, the dependent variable of our regression, the VIX data, is obtained in the corresponding site of *yahoo!*

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<sup>1</sup> Institute for Health Metrics and Evaluation, located in the University of Washington, Seattle, US

<sup>2</sup> The data and the sessions are referenced from the thematic website The US Economy and COVID-19: Economic Factors in Search ([https://trends.google.com/trends/story/US\\_cu\\_mcuHBXIBAABsTM\\_en](https://trends.google.com/trends/story/US_cu_mcuHBXIBAABsTM_en))

Finance<sup>3</sup>. The VIX values are taken as their natural logarithms during the regressions.

Note that, the sample data is collected from Feb 10 to Dec 28, 2020, which is recorded weekly.

## (2) Assumptions

When manipulating the data for Google Trend, there are values '<1' as shown in Table 1, for instance:

Date	Unemployment Benefits	Food Stamps	Food Bank	Stimulus
2020/2/10	3	24	29	<1
2020/2/17	4	23	32	<1
2020/2/24	4	20	31	<1
2020/3/2	4	19	31	<1

Table 1: The table shows some of the data of the database. In this example, there are cells containing '<1' under the column named 'Stimulus'.

They are replaced by simply zeros for their unexpected string data type. For the dependent variable, the highest peak values of VIX are considered weekly as the dependent variables, and then we take the natural logarithms of them.

## (3) Collinearity and VIF

Before performing regressions, some of the potential terms may be dismissed because of the high collinearity between them, which causes the poor characteristics of the data. To detect and mitigate the collinearity, one may use the variation inflation factor (*VIF*) of term *i*:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where  $R_i^2$  is the coefficient of determination of the auxiliary regression model?

$$x_i = a_0 + a_1x_1 + a_2x_2 + \dots + a_{i-1}x_{i-1} + a_{i+1}x_{i+1} + \dots + a_kx_k + \varepsilon$$

and where  $\varepsilon$  is the random error, *k* is the number of terms being considered. If  $VIF_i \geq 10$ , then term *i* indicates high collinearity, and thus we discard the terms with such high VIFs.

## (4) Research Process

Consider a collection of terms to be included in the regression model. Define the collection of all the terms considered in the final regression as *LIST*, then we update *LIST* recursively by the procedure shown in Figure 1:

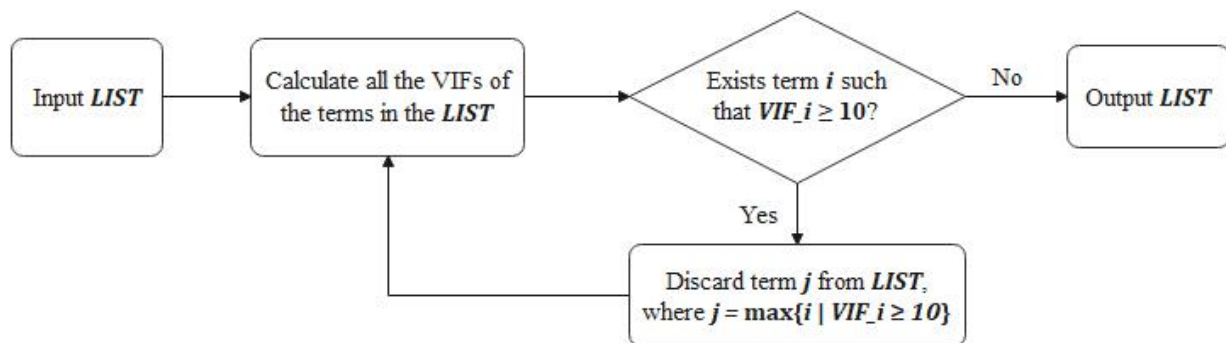


Figure 1: The procedure of obtaining the list of explanatory variables in the regression, *LIST*

After obtaining the *LIST*, namely after choosing the terms considered in the regression, we then do the regression (OLS) based on the data of the terms in *LIST*. There are further steps after the regression:

- 1) To include an autocorrelation term (AR (1) model) to detect if the series is autocorrelated.
- 2) To perform a stepwise regression forward to see if a better model could be obtained. If the stepwise regression model fits better, then we would consider the stepwise one.

<sup>3</sup> Site for CBOE Volatility Index: <https://finance.yahoo.com/quote/%5EVIX?p=%5EVIX>, assessed on 27 February 2021.

## (5) Additional Tasks and Robustness

As mentioned in the literature review, most of the researches, especially the ones with reports of the pandemic involved, are based on the samples collected in the very first months, while this research is based on a whole-year sample. Therefore, one important task is to verify whether the reports are still a significant factor to the volatility during the whole year, or the second-half year.

To detect whether the results are robust, regressions based on the data in the first-half (from Feb 10 to Jul 13, 2020) or the second-half year (from July 20 to Dec 28, 2020) are performed.

Furthermore, if necessary, we could perform the regressions based on the data of some terms solely. For instance, we could perform the regression where the explanatory variables are just the variables in session N.

## (6) Summary of the Sessions of the Research

Table 2 shows the notations of the sessions of the research, each of which has the similar process mentioned in the ‘Research Process’ Part. Note that, not all the sessions are going to be investigated.

Sector/Time	From Feb 10 to Dec 28, 2020 (W)	From Feb 10 to Jul 13, 2020 (F)	From July 20 to Dec 28, 2020 (L)
The reports for the pandemic (N)	NW (Supplementary Tests)	NF (Supplementary Tests)	NL (Supplementary Tests)
The medical resources needed (M)	MW (Supplementary Tests)	MF (Supplementary Tests)	ML (Supplementary Tests)
Google Trends (G)	GW	GF	GL
All terms (A)	AW (The Main Research)	AF (Robustness Test)	AL (Robustness Test)

Table 2: The summary and notations of the sessions in the research

## 3. Results

In the AW session, after the procedure of discarding terms with high VIFs, the terms in the LIST are New Deaths, Nasdaq, GDP, CPI, Recession, Debt, Food Bank, Stimulus, Coronavirus, Stock Market, Unemployment, and Vaccine. The results of the regressions are shown in Appendix A.

Similarly, in the AF session, namely when we consider all potential factors from Feb 10 to Jul 13, 2020, after the procedure of discarding terms with high VIFs, the terms in the LIST are New Cases, New Deaths, Infection Rate, GDP, Recession, Debt, Stock Market, and Vaccine. The results of the regressions are shown in Appendix B.

In the AL session, namely when we consider all potential factors from Jul 20 to Dec 28, 2020, after the procedure of discarding terms with high VIFs, the terms in the LIST are Nasdaq, NYSE, VIX, GDP, CPI, Recession, Mortgage Forbearance, Food Stamps, Stimulus, Coronavirus, Stock Market, Unemployment, and Vaccine. The results of the regressions are shown in Appendix C.

There are additional regressions based on the reports of the pandemic from Feb 10 to Dec 28, from Feb 10 to Jul 13, and from Jul 20 to Dec 28, 2020, as shown in Appendices D, E, and F.

Finally, the results in Appendix G are the estimates of the regressions based on the number of medical resources needed only, where the LIST in all three periods contains the term Invasive Ventilators Needed only, after filtering.

## 4. Discussion

### (1) The Main Research: The AW Session

Now consider the AW session, i.e., the overall potential explanatory variables from Feb 10 to Dec 28, 2020. From the results of Appendix, A, we observe that:

In model 1, the constant term is highly significant and positive, signaling that these terms somewhat underestimate the

VIX values. Since the autocorrelation term in model 2 is highly significant, and compared to the first one, after including the correlation, the estimate and the significance of the constant term is lessened, indicating that the autocorrelation does interpret a portion of the VIX values, then here we have to include the autocorrelation term. However, in the second model, only the constant and the autocorrelation term are significant.

After stepwise regression forward based on model 2, the only terms left is constant, Coronavirus and the lagged term, all of which are highly significant, and the model has reflected in model 3 column. The RMSE of model 3 is smaller than the second one, indicating a better fitting. The estimates are more focused and the variances are less inflated, as a result of the stepwise regression.

Therefore, it is concluded that the term Coronavirus affects the VIX significantly, and the evolution of VIX is dynamic.

## (2) Robustness: The AF Session

Recall that the table in Appendix B presents the results of the AF session, namely, the overall potential explanatory variables from Feb 10 to Jul 13, 2020.

In model 1, the only significant terms are constant and stock market term. After including the lagged term, although the constant term becomes insignificant, the only significant term turns to the lagged term, which is merely significant at a 10% level. However, since the R-squared and F-statistic are enlarged, p-value and RMSE are diminished, then model 3 is better than model 1, that is, it is a good choice to include the autocorrelation term.

We may consider a stepwise regression forward based on model 1, shown in model 2. Apart from the constant, the term stock market is retained, which is significant. Based on models 2 and 4, we observe whether the regression model involved with Stock Market and the lagged term is a good fitting, as shown in model 5. Both of them are significant, and the RMSE is the smallest among the five models, indicating the best fitting.

Therefore, we could conclude that in the first period, the term Stock Market affects the VIX, although not significantly. The evolution of VIX values in the first period is proved to be dynamic, although the lagged term is not as significant as the one in the whole period.

## (3) Robustness: The AL Session

Appendix C displays the results of the AL session, namely, the overall potential explanatory variables from July 20 to Dec 28, 2020. The only conclusion one could obtain is that from Jul 2020 to Dec 28, 2020, the evolution of the VIX values is probably not dynamic, and any of the terms we investigate is insufficient to have a significant effect on the VIX values.

## (4) Why Doing Supplementary Tasks

By the results of AW, AL, and AF sessions, we may notice that most of the potential terms are derived from Google Trend: In the AW session, only one of them is not a Google Trend term, and in the AL session, all the potential terms are Google Trend terms, which is a consequence of the filtering by VIFs. Therefore, the conclusions are always involved with the significance of the Google Trend terms, instead of the number of reports, or the number of medical resources needed.

More scholars have noticed how Google Trend data being highly reflective of reality. Sharma and Sharma <sup>[10]</sup> (2020) found that there is a positive correlation between the number of cases of COVID-19 and the Google Trend values in some major countries from Mar 1 to Apr 10, 2020. Analogously, Xu and Berkely <sup>[11]</sup> (2014) concluded that “the weekly stock price changes within different intervals of news values behave in the same way as what we expect” (p. 18).

On the one hand, there are multiple pieces of research claiming the significant effects of the number of reports on the volatility, as shown in the literature review, most of which are based on the data in the very first months. Therefore, it is necessary to verify whether this conclusion is valid for a much longer period.

VIF Value			
Period	W	F	L
Number of All Beds Needed	181.2	108.4	1878.6
Number of ICU Beds Needed	218.3	216.2	1097.6
Number of Invasive Ventilators Needed	12.8	50.1	178.1

Table 3: The VIF values of the terms of number of medical resources when they are considered together. All of them exceed the value 10, therefore they are jointly highly collinear.

On the other hand, the number of medical resources is always discarded in the filtering process. The first reason for this is the high collinearity of the terms in this sector, as shown in Table 3. The second reason is that these terms are always collinear with other terms, as shown in Table 4.

VIF Value					
Period	W	F	L		
New Deaths	10.9	12.3	\	\	\
Number of Invasive Ventilators Needed	10.9	12.3	8.4	14.3	10.8
CPI	\	\	\	3.1	\
Food Stamps	\	\	\	\	1.7
Coronavirus (Thematic)	\	\	2.5	2.5	3.1
Stock Market (Thematic)	\	\	1.2	1.7	1.3
Unemployment (Thematic)	\	\	1.3	1.9	1.3
Vaccine (Thematic)	\	\	6.2	7.7	6.4

Table 4: The VIF values of some terms when they are considered together. The backslashes mean the terms are not considered in the corresponding situation.

### (5) Supplementary: Number of Reports

In this supplementary task, we perform the regressions whose independent variables are merely the lagged term and any one of the terms in sector N, as shown in Appendices D, E and F, which correspond to the whole, former and later period respectively.

In the whole period, we observe that the number of new testing has a significant impact on the evolution of VIX, which is a dynamic process. The number of new cases, new deaths, and infection rate have an impact on VIX as well, although not as significant as the number of tests.

However, in the former period, only the number of new cases is considered as a slight significant factor of the VIX, which is a dynamic process. In the later period, the results are inconclusive, which is consistent with the conclusion in the AL session.

### (6) Supplementary: Number of Medical Resources Needed

In this supplementary task, we perform the regressions whose independent variables are merely the lagged term and the Number of Invasive Ventilators Needed term, since it always has the least VIF among the three variables in this sector (see Table 3), and the estimates are presented in Appendix G. In summary, the number of medical resources has impacts on the VIX values. Note that in the later period, the Number of Medical Resources has a significant impact on VIX, which seems inconsistent with the conclusion in the AL session. Nevertheless, the R-squared value for the model is small (0.239), indicating the fitting is not good as expected.

## 5. Conclusion

Recall that, the study is based on the data from Feb 10 to Dec 28, 2020, and we split the period into two further periods for further researches - one is from Feb 10 to Jul 13, 2020, the other is from Jul 20 to Dec 28.

In conclusion, during the whole period, people's focus on coronavirus is the most significant factor that induces the volatility, and the VIX values evolve dynamically. Additionally, we deduce that the number of new tests is a significant factor for the VIX when being regressed solely. The number of new cases, new deaths, accumulated deaths, infection rate, and invasive ventilators are proved to have an impact on VIX as well when being regressed solely, while their impact is not significant as the number of tests.

Further, in the former period, people's focus on the stock market, the number of invasive ventilators needed, and the number of new cases is proved to affect the volatility, though not significantly. However, in the later period, none of the potential factors are shown to be a factor to the volatility, and the VIX moves are not autocorrelated.

Moreover, the data for the number of medical resources need – the number of all beds needed, ICU beds needed, and

invasive ventilators needed are jointly highly collinear, therefore the conclusions above are accurate for the number of (ICU) beds instead of invasive ventilators needed. Further, these data are highly collinear with the number of new deaths in the whole and the former period.

## 6. Pros, Cons, and Recommendations

During the research, it is observed that the data from Google Trends is, to a certain extent, highly reflective of reality – not only people’s opinions and concerns but also what search term itself corresponds to, which needs more researches to be verified.

The constants of the models are still highly significant, implying the models are still underestimating, which means more scholars are needed for their dedication on this topic, especially for the cases in the later period. It is undeniable that the situation becomes more complicated in the later period – for instance, the society has become much more divisive in the US, and more social issues, and these factors are to be investigated. And certainly, the conclusions derived from the research may not be robust - the pandemic continues, and more issues may occur and have an impact on the volatility.

Despite the limitations, the research is helpful for the causes of the volatility during the COVID-19. It paves the way for further studies focusing on other potential factors, especially for the researches based on the period after the very first months of the pandemic. With this study, it is important not only to control the further spread of the pandemic but also to find approaches to stabilize people’s emotions towards the aspects of life which are affected by the pandemic.

## References

- [1] Wagner, A. F. (2020). What the stock market tells us about the post-COVID-19 world. *Nature Human Behaviour*, 4(5), 440-440. doi:10.1038/s41562-020-0869-y.
- [2] Devpura, N., & Narayan, P. (2020). Hourly Oil Price Volatility: The Role of COVID-19. *Energy RESEARCH LETTERS*. doi: 10.46557/001c.13683.
- [3] Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, 101748.
- [4] Albulescu, C. (2020). Coronavirus and Financial Volatility: 40 Days of Fasting and Fear. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3550630.
- [5] Baker, S., Bloom, N., Davis, S., Kost, K., Sammon, M., & Viratyosin, T. (2020). The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*. doi: 10.1093/rapstu/raaa008.
- [6] Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, 100343.
- [7] Albulescu, C. (2020). COVID-19 and the United States financial markets’ volatility. *Finance Research Letters*, 101699. doi: 10.1016/j.frl.2020.101699.
- [8] Stephanos, P., Athanasios P., F., Dimitris, K., & Dimitris, D. (2020). Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis. *Munich Personal Repec Archive*, (100020).
- [9] Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, 28(1), 1-32.
- [10] Sharma, M., & Sharma, S. (2020). The Rising Number of COVID-19 Cases Reflecting Growing Search Trend and Concern of People: A Google Trend Analysis of Eight Major Countries. *Journal of Medical Systems*, 44(7). doi: 10.1007/s10916-020-01588-5.
- [11] Xu, S. Y., & Berkely, C. U. (2014). Stock price forecasting using information from Yahoo finance and Google trend. *UC Berkeley*.

## Appendices

### A. The regression results for the AW session

Estimates			
	Model 1	Model 2	Model 3
<b>Constant</b>	2.913*** (0.44988)	1.199* (0.753)	0.573** (0.284)
<b>New Deaths</b>	$-9.85 \times 10^{-6}$ ( $1.92 \times 10^{-5}$ )	$-3.82 \times 10^{-6}$ ( $1.77 \times 10^{-5}$ )	
<b>Nasdaq</b>	$-3.04 \times 10^{-4}$ ( $4.22 \times 10^{-3}$ )	$-1.51 \times 10^{-3}$ ( $3.90 \times 10^{-3}$ )	
<b>GDP</b>	$3.17 \times 10^{-3}$ ( $3.00 \times 10^{-3}$ )	$5.15 \times 10^{-4}$ ( $2.92 \times 10^{-3}$ )	
<b>CPI</b>	$4.23 \times 10^{-3}$ ( $4.11 \times 10^{-3}$ )	$2.45 \times 10^{-3}$ ( $3.83 \times 10^{-3}$ )	
<b>Recession</b>	$-1.69 \times 10^{-3}$ ( $5.33 \times 10^{-3}$ )	$3.50 \times 10^{-4}$ ( $4.95 \times 10^{-3}$ )	
<b>Debt</b>	$-4.88 \times 10^{-3}$ ( $5.88 \times 10^{-3}$ )	$-3.32 \times 10^{-4}$ ( $5.65 \times 10^{-3}$ )	
<b>Food Bank</b>	$9.60 \times 10^{-4}$ ( $4.22 \times 10^{-3}$ )	$1.01 \times 10^{-3}$ ( $3.87 \times 10^{-3}$ )	
<b>Stimulus</b>	$5.23 \times 10^{-4}$ ( $3.66 \times 10^{-3}$ )	$-5.04 \times 10^{-4}$ ( $3.38 \times 10^{-3}$ )	
<b>Coronavirus (Thematic)</b>	$-3.05 \times 10^{-3}$ ( $3.83 \times 10^{-3}$ )	$-3.84 \times 10^{-3}$ ( $3.53 \times 10^{-3}$ )	$-3.95 \times 10^{-3}$ *** ( $1.34 \times 10^{-3}$ )
<b>Stock Market (Thematic)</b>	0.018*** ( $4.68 \times 10^{-3}$ )	$6.62 \times 10^{-3}$ ( $6.01 \times 10^{-3}$ )	
<b>Unemployment (Thematic)</b>	$6.63 \times 10^{-3}$ ( $3.75 \times 10^{-3}$ )	$2.29 \times 10^{-3}$ ( $3.79 \times 10^{-3}$ )	
<b>Vaccine (Thematic)</b>	$4.24 \times 10^{-3}$ ( $8.19 \times 10^{-3}$ )	$3.47 \times 10^{-3}$ ( $7.52 \times 10^{-3}$ )	
<b>AR (1)</b>		0.605*** (0.223)	0.893*** (0.085)
<b>R-squared</b>	0.698	0.754	0.716
<b>F-statistic vs. Constant</b>	6.56	7.76	55.4
<b>p-value</b>	$7.01 \times 10^{-6}$ ***	$9.81 \times 10^{-7}$ ***	$9.56 \times 10^{-13}$ ***
<b>RMSE</b>	0.227	0.209	0.194

\*, \*\*, \*\*\*: significant at 10%, 5% and 1%



## B. The regression results for the AF session

Estimates					
	Model 1	Model 2	Model 3	Model 4	Model 5
<b>Constant</b>	3.411*** (0.782)	3.269*** (0.0964)	1.343 (1.386)	0.972** (0.455)	1.806*** (0.586)
<b>New Cases</b>	$-7.68 \times 10^{-7}$ ( $1.64 \times 10^{-6}$ )		$-3.22 \times 10^{-7}$ ( $1.45 \times 10^{-6}$ )		
<b>New Deaths</b>	$-1.13 \times 10^{-6}$ ( $1.99 \times 10^{-5}$ )		$2.72 \times 10^{-6}$ ( $1.77 \times 10^{-5}$ )		
<b>Infection Rate</b>	2.455 (2.213)		$4.23 \times 10^{-8}$ ( $1.45 \times 10^{-7}$ )		
<b>GDP</b>	$-1.33 \times 10^{-3}$ (0.0168)		$8.18 \times 10^{-3}$ (0.0165)		
<b>Recession</b>	$-6.80 \times 10^{-3}$ ( $7.63 \times 10^{-3}$ )		$-1.59 \times 10^{-3}$ ( $6.20 \times 10^{-3}$ )		
<b>Debt</b>	$-3.64 \times 10^{-3}$ (0.0138)		$-2.96 \times 10^{-3}$ (0.0135)		
<b>Stock Market (Thematic)</b>	0.0168** ( $6.51 \times 10^{-3}$ )	0.0143** ( $2.53 \times 10^{-3}$ )	$9.00 \times 10^{-3}$ ( $7.88 \times 10^{-3}$ )		$7.36 \times 10^{-3}$ * ( $3.57 \times 10^{-3}$ )
<b>Vaccine (Thematic)</b>	0.0262 (0.0728)		-0.0357 (0.0689)		
<b>AR(1)</b>			0.601* (0.310)	0.744*** (0.122)	0.455** (0.180)
<b>R-squared</b>	0.672	0.606	0.727	0.638	0.701
<b>F-statistic vs. Constant</b>	3.59	32.3	3.84	37	23.5
<b>p-value</b>	0.0179**	$1.22 \times 10^{-5}$ ***	0.0143**	$4.94 \times 10^{-6}$ ***	$5.69 \times 10^{-6}$ ***
<b>RMSE</b>	0.292	0.277	0.277	0.251	0.233
*, **, ***: significant at 10%, 5% and 1%					

### C. The regression results for the AL session

Estimates			
	Model 1	Model 2	Model 3
<b>Constant</b>	3.785*** (0.686)	0.54907 (3.00)	3.699*** (0.113)
<b>Nasdaq</b>	- 0.0156* ( $8.19 \times 10^{-3}$ )	- 0.0132 ( $8.37 \times 10^{-3}$ )	
<b>NYSE</b>	- $5.02 \times 10^{-3}$ (0.117)	0.0117 (0.0190)	
<b>VIX</b>	0.0185* ( $9.35 \times 10^{-3}$ )	$2.28 \times 10^{-3}$ (0.0173)	
<b>GDP</b>	$2.32 \times 10^{-4}$ ( $2.52 \times 10^{-3}$ )	- $1.19 \times 10^{-3}$ ( $2.81 \times 10^{-3}$ )	
<b>CPI</b>	$9.16 \times 10^{-4}$ ( $3.16 \times 10^{-3}$ )	- $1.66 \times 10^{-3}$ ( $3.89 \times 10^{-3}$ )	
<b>Recession</b>	- $4.01 \times 10^{-3}$ (0.0530)	0.0289 (0.0602)	
<b>Mortgage Forbearance</b>	0.0279 (0.0208)	0.0375 (0.0224)	
<b>Food Stamps</b>	0.0171 (0.0158)	0.0277 (0.0183)	
<b>Stimulus</b>	- $4.72 \times 10^{-3}$ ( $4.23 \times 10^{-3}$ )	- $8.09 \times 10^{-3}$ ( $5.17 \times 10^{-3}$ )	
<b>Coronavirus (Thematic)</b>	- $5.86 \times 10^{-3}$ ( $4.96 \times 10^{-3}$ )	- 9.24 $\times 10^{-3}$ * ( $5.78 \times 10^{-3}$ )	- $6.66 \times 10^{-3}$ * ( $2.13 \times 10^{-3}$ )
<b>Stock Market (Thematic)</b>	- 0.0139 (0.0214)	- 0.0248 (0.0234)	
<b>Unemployment (Thematic)</b>	- $3.23 \times 10^{-3}$ ( $6.47 \times 10^{-3}$ )	- $2.85 \times 10^{-3}$ ( $6.41 \times 10^{-3}$ )	
<b>Vaccine (Thematic)</b>	$5.00 \times 10^{-3}$ ( $5.84 \times 10^{-3}$ )	$8.70 \times 10^{-3}$ ( $6.67 \times 10^{-3}$ )	
<b>AR(1)</b>		0.832 (0.752)	
<b>R-squared</b>	0.731	0.764	0.308
<b>F-statistic vs. Constant</b>	2.09	2.08	9.79
<b>p-value</b>	0.123	0.136	$4.89 \times 10^{-3}$ ***
<b>RMSE</b>	0.129	0.128	0.14
*, **, ***: significant at 10%, 5% and 1%			

### D. The regression results for the NW session

Estimates							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
<b>Constant</b>	1.012*** (0.328)	1.056*** (0.338)	0.871*** (0.307)	1.215*** (0.346)	1.221*** (0.342)	1.064*** (0.340)	0.704*** (0.296)
<b>New Cases</b>	- 1.55 $\times 10^{-7**}$ ( $7.76 \times 10^{-8}$ )						
<b>Accumulated Cases</b>		- 1.32 $\times 10^{-8**}$ ( $6.56 \times 10^{-9}$ )					
<b>New Deaths</b>			- $1.11 \times 10^{-5*}$ ( $6.25 \times 10^{-6}$ )				
<b>Accumulated Deaths</b>				- 8.68 $\times 10^{-7**}$ ( $3.42 \times 10^{-7}$ )			
<b>New Tests</b>					- 2.72 $\times 10^{-8***}$ ( $1.03 \times 10^{-8}$ )		
<b>Accumulated Tests</b>						- 1.04 $\times 10^{-9}$ ( $5.17 \times 10^{-10}$ )	
<b>Infection Rate</b>							- 1.077* (0.657)
<b>AR(1)</b>	0.732*** (0.0889)	0.720 (0.0910)	0.776 (0.0840)	0.691*** (0.0908)	0.690*** (0.0900)	0.720*** (0.0913)	0.827*** (0.0851)
<b>R-squared</b>	0.691	0.691	0.685	0.706	0.709	0.691	0.682
<b>F-statistic vs. Constant</b>	49.1	49.2	47.9	52.8	53.6	49.2	47.2
<b>p-value</b>	$6.19 \times 10^{-12***}$	5.92 $\times 10^{-12***}$	$9.07 \times 10^{-12***}$	$2.05 \times 10^{-12***}$	1.59 $\times 10^{-12***}$	5.93 $\times 10^{-12***}$	1.13 $\times 10^{-11***}$
<b>RMSE</b>	0.203	0.202	0.204	0.197	0.196	0.202	0.205
*, **, ***: significant at 10%, 5% and 1%							

### E. The regression results for the NF session

Estimates							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
<b>Constant</b>	1.077*** (0.431)	1.163** (0.464)	1.004** (0.447)	1.178** (0.466)	1.150** (0.346)	1.120*** (0.469)	0.836* (0.473)
<b>New Cases</b>	$-8.77 \times 10^{-7}$ * ( $4.53 \times 10^{-7}$ )						
<b>Accumulated Cases</b>		$-7.28 \times 10^{-8}$ ( $5.11 \times 10^{-8}$ )					
<b>New Deaths</b>			$-1.31 \times 10^{-5}$ ( $9.67 \times 10^{-6}$ )				
<b>Accumulated Deaths</b>				$-1.45 \times 10^{-6}$ ( $1.01 \times 10^{-6}$ )			
<b>New Tests</b>					$-4.81 \times 10^{-8}$ ( $3.17 \times 10^{-8}$ )		
<b>Accumulated Tests</b>						$-4.70 \times 10^{-9}$ ( $4.03 \times 10^{-9}$ )	
<b>Infection Rate</b>							$-1.040$ (1.012)
<b>AR (1)</b>	0.749*** (0.115)	0.713 (0.121)	0.756*** (0.120)	0.710 (0.122)	0.719*** (0.120)	0.718*** (0.123)	0.820*** (0.135)
<b>R-squared</b>	0.695	0.671	0.668	0.672	0.675	0.661	0.656
<b>F-statistic vs. Constant</b>	22.8	20.4	20.1	20.5	20.8	19.5	19.1
<b>p-value</b>	$7.01 \times 10^{-6}$ ***	$1.48 \times 10^{-5}$ ***	$1.61 \times 10^{-5}$ ***	$1.45 \times 10^{-5}$ ***	$1.31 \times 10^{-5}$ ***	$2.02 \times 10^{-5}$ ***	2.33 $\times 10^{-5}$ ***
<b>RMSE</b>	0.236	0.245	0.246	0.245	0.243	0.249	0.25

\*, \*\*, \*\*\*: significant at 10%, 5% and 1%

## F. The regression results for the NL session

Estimates							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
<b>Constant</b>	2.057*** (0.694)	1.826** (0.673)	2.030** (0.757)	1.769 (0.686)	2.017*** (0.701)	1.759 (0.667)	2.194*** (0.700)
<b>New Cases</b>	$-9.95 \times 10^{-8}$ ( $7.22 \times 10^{-8}$ )						
<b>Accumulated Cases</b>		$-6.59 \times 10^{-9}$ ( $7.28 \times 10^{-9}$ )					
<b>New Deaths</b>			$-8.45 \times 10^{-6}$ ( $8.51 \times 10^{-6}$ )				
<b>Accumulated Deaths</b>				$-3.17 \times 10^{-7}$ ( $5.98 \times 10^{-7}$ )			
<b>New Tests</b>					$-1.94 \times 10^{-8}$ ( $1.57 \times 10^{-8}$ )		
<b>Accumulated Tests</b>						$-4.59 \times 10^{-10}$ ( $6.37 \times 10^{-10}$ )	
<b>Infection Rate</b>							$-1.554^*$ (0.943)
<b>AR (1)</b>	0.405* (0.200)	0.471** (0.193)	0.414*** (0.214)	0.495 (0.192)	0.437** (0.195)	0.490 (0.192)	0.384* (0.196)
<b>R-squared</b>	0.324	0.291	0.296	0.146	0.313	0.281	0.347
<b>F-statistic vs. Constant</b>	5.03	4.3	4.41	4.01	4.78	4.1	5.59
<b>p-value</b>	0.0164**	0.0272**	0.0251**	0.0336**	0.0194**	0.0315**	0.0113***
<b>RMSE</b>	0.141	0.145	0.144	0.146	0.142	0.146	0.139

\*, \*\*, \*\*\*: significant at 10%, 5% and 1%

**G. The regression results for the MW, MF and ML sessions**

<b>Estimates</b>			
<b>Period</b>	<b>W</b>	<b>F</b>	<b>L</b>
<b>Constants</b>	0.887*** (0.296)	0.972** (0.296)	2.180*** (0.296)
<b>Invasive Ventilators Needed</b>	$-2.61 \times 10^{-6}$ ** ( $1.08 \times 10^{-6}$ )	$-3.34 \times 10^{-6}$ * ( $1.83 \times 10^{-6}$ )	$-3.12 \times 10^{-6}$ ** ( $1.19 \times 10^{-6}$ )
<b>AR(1)</b>	0.781*** (0.0812)	0.776*** (0.117)	
<b>R-squared</b>	0.702	0.689	0.239
<b>F-statistic vs. Constant</b>	51.8	22.2	6.89
<b>p-value</b>	$2.73 \times 10^{-12}$ ***	$8.35 \times 10^{-6}$ ***	0.015**
<b>RMSE</b>	0.199	0.238	0.146
*, **, ***: significant at 10%, 5% and 1%			