Global Economic Impact of the 2019 Novel Coronavirus (2019-nCoV) Pandemic

Yijia Ren

Abstract—**The current 2019 Novel Coronavirus (2019-nCoV) outbreak is estimated to have much larger economic effects because of the global response that involved shutting down of businesses and, in some cases, mandatory curfews and quarantines. This research aims to analyze and predict the global impact of the 2019 Novel Coronavirus or 2019-nCoV on global markets, as measured by Gross Domestic Product (GDP), employment, consumer spending (retail sales) and financial markets. It provides a projection of where the global stock markets may be heading for the latter half of 2020 based upon projected GDP, employment, and consumer spending. The research also considers the impact of previous virus outbreaks, such as the SARS crisis which created approximately $40 billion in economic damage. White points out that sectors such as travel and leisure in addition to energy and retail may suffer significant losses as a result of travel bans and lack of economic activity. The same is true of the restaurant industry, and most industries will be negatively impacted to some extent. Equipped with financial projections, an investor would be able to identify strategies to protect (or benefit from) their assets in the event of a worst-case scenario.**

Index Terms—**Coronavirus, economic impact, global pandemic, economic projections.**

I. Introduction

The economic implications of COVID-19 have become apparent over the course of the last few weeks as industries and economic sectors come to terms with the setbacks caused by the pandemic. The key reason why COVID-19 has had unprecedented impact on the global economy is largely due to a reduction in consumer purchasing power as laborers had to vacate their jobs to conform to the quarantine protocols. As such, many future prices based on oil and gas derivatives have experienced negative returns [1] due to a decline in market demand. Other economic sectors have suffered a similar fate as consumers changed their spending preferences at the height of the pandemic.

Therefore, it becomes important to establish potential models of how the impact of the virus will unfold over the rest of 2020 and how investors and citizens should respond to the associated risks. For that reason, the paper engages in an exploration of models that can predict the economic effect of pandemics and other unpredictable events on the economic output. The models will serve as predictors for the future behavior of the virus and the associated economic losses that could occur. Three econometric models were created to inspect the relationship between economic variables and global equities, in order to provide investors with an idea of what the economic impact and financial impact might be. The models were based upon published estimates of GDP, employment, and retail sales of well-known financial institutions. The data itself covers the years 1960 through 2019 for actuals or estimated actuals, with the 2020 estimates stemming from national and international institutions and their professional economics network.

II. Data Collection

Data was collected on four variables subject to evaluate the economic effect of COVID-19. These low to high-frequency measures are in constant flux, and as such, should be considered as subject to change at any given moment. The data was captured on May 1, 2020 to provide the most recent figures.

The first source was an open source daily COVID-19 tracker across countries. Countries report this information voluntarily[1]. A time-series plot by country across time is given in the following Fig. 1, with a geographic view following in Fig. 2. These were created using RStudio and Tableau. Based upon this reported data, the number of confirmed COVID-19 cases has risen from virtually 0 at the start of 2020 to close to 3.1 million as of writing. The country with the largest reported number of cases is the United States at just over 1 million, followed by Spain at approximately 475,000 and Italy at just over 200,000.

It is important to note that these charts were created based upon reported, publicly available data. The actual counts may have been reported inaccurately in some cases, estimates of which can vary widely [2].

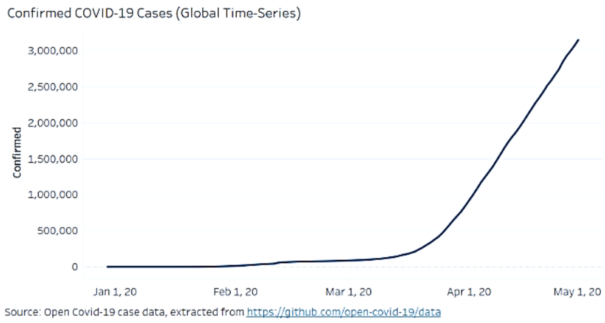

Fig. 1. Confirmed COVID-19 cases (global time-series).

With the COVID-19 cases as the background, the research involved gathering data on the four variables that would be incorporated into an econometric model. The first of these four variables is the national Gross Domestic Product (GDP).

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The author is with the University of Southern California, USA (e-mail: Sissi.renmfe@gmail.com).

[1] The data are available here: https://github.com/open-covid-19/data.

Gross domestic product is the total value realized in an economy. The measure can be broken down by industry, country, sub-measures, or other detail. In this research, the broad GDP definition, as stated above, is used. There is at least one disadvantage to using GDP as a measure of the economic impact of the COVID-19 – the GDP figures are reported with a strong lag. For instance, GDP for the United States, a country that releases data on economic activity on as close to real-time basis as most any other developed country, still comes with a one-month lag for the prior quarter. This means that GDP for the United States for the months January through March (the first quarter, or Q1) was just released in the last week of April. With this acknowledged, GDP is still the largest measure of economic activity commonly used by the market and economists, and as such, is included as a measure of economic impact in this study. The following Fig. 3 plots global GDP from 1960 to 2019 based upon information gathered by the World Bank [3]. The data reported in Fig. 3 is converted into dollars using current dollars. Overall, global GDP has gone from $1.4 trillion in 1960 to $85.9 trillion at the end of 2018. Using a 5.3% growth rate for 2019, total global GDP going into the COVID-19 period was $90.5 trillion. The International Monetary Fund (IMF) recently projected that global growth would decline by 3% in 2020 assuming the effects of COVID-19 on economic activity are diminished soon and general growth resumes [4].

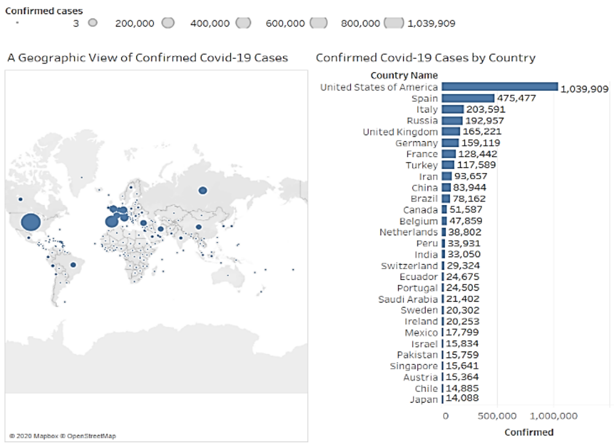

Fig. 2. A geographic view of confirmed Covid-19 cases and confirmed cases by country.

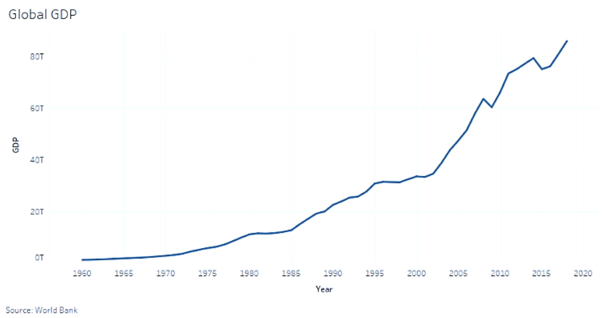

Fig. 3. Global GDP.

It is important to note that the effect of COVID-19 on global GDP is not equal across countries. As of writing, high income countries (European/United States/select Asian countries) made up $54.2 trillion of the $85.9 trillion. The largest single country for GDP is the United States at $20.4 trillion and the largest economic union is the European Union at $18.8 trillion. Generally, the effects of COVID-19 will be felt strongest among the higher income countries where restrictions on economic activity have been the most pronounced. Some analysts have suggested that GDP in the European Union and the United States could drop by as much as 30% (or even more) in the second quarter of 2020 due to the shutdown of business activity [5]. For the VAR models, a 30% drop in global GDP in the second quarter is used, followed by rapid rebounds in the third and fourth quarter so that global GDP for the entire 2020 year is down by 4%.

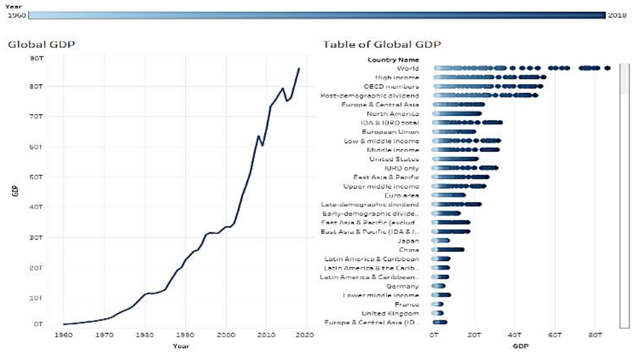

Fig. 4. Table of global GDP.

The second economic indicator variable employed in the analysis was employment across countries. The following Fig. 5 has global employment from 1960 to 2020. This estimate is based upon information gathered from the World Bank and other sources to derive the overall estimate. Unsurprisingly, global employment varies based upon the economic cycle. The initial estimate of global employment was 913 million in 1960. This might seem low to some but is likely not far off from the actual employment base because it was after this when many women entered the workforce and it was before the well-known Baby Boom generation of the 1960s. Global employment grew quickly into the 1980s, dropping from 2.4 billion in 1980 to 1.9 billion in 1985 because of the global hyperinflation forces that led to a severe global economic downturn. Some of this might also be due to data gathering errors, in that employment statistics were not as well collected back then as they are today. Global employment rose again through the mid-1990s, peaking in 1995 at 3.2 billion. After some weakness in the economy, global employment began to rise again in 2002. By 2019, global employment had reached 4.2 billion. That number is likely to drop by the end of 2020 to perhaps 4.1 billion as firms across the world take time to recovery lost momentum from the effects of COVID-19. The question of this paper is how this loss in 100 million jobs will affect the other economic variables in addition to global financial markets.

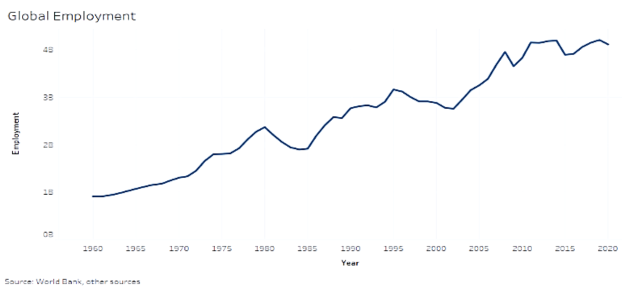

Fig. 5. Global employment.

The third economic indicator variable was consumer spending (retail sales) across countries. Of the measures presented in this paper, this is the measure of least confidence because countries report this information differently and, although attempts were made to harmonize the data, it is not necessarily completely harmonized. For instance, some countries may include business investment in consumer spending estimates, whereas others may attempt to back this information out before reporting the information. Overall, based upon the estimated information, global consumer spending has gone from $523 million in 1960 to a high of $12.7 trillion in 2019 (this $12.7 trillion is almost assuredly too low, but can still act as a reasonable proxy for this study). Unsurprisingly, the effects of COVID-19 will be felt in the global consumer spending world. The estimate presented in the following Fig. 6 has global spending dropping from $12.7 trillion to $12.1 trillion in 2020. Two other economic cycles have exhibited weakness in consumer spending during business cycle weaknesses. These two are 2009 and 2015. The 2009 weakness should be unsurprising to anyone who lived through the global financial crisis. The 2015 period was a mini-recession across the globe that was mainly felt in consumer spending but was not a global recession. This measure is an important determinant of global stock markets.

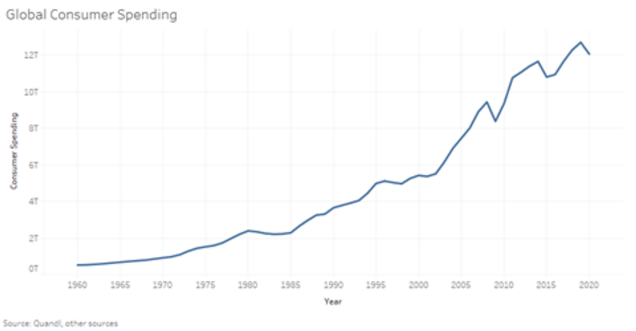

Fig. 6. Global consumer spending.

The fourth economic indicator variable was the performance of financial markets. This is the main dependent variable in the models. As shown in the following Fig. 7, global stocks have done incredibly well in recent years. Since 2010, global stocks are up over 200%. If one looks at the period all the way back to 1960, the rise in stocks is even more amazing, up over 5,000%. The recent sharp increases met a grinding halt in March 2020, with global stocks down around 40%. Some of that has been gained back in recent weeks, although overall global stocks are still down around 20% from their all-time highs in 2019. Obviously, this is a fascinating question for stock market observers. The effects of COVID-19 are being felt in virtually every corner of the globe, but global stock markets appear to have moved past the weakness to expect perhaps the greatest recovery on record. It, of course, remains to be seen whether the strong picture painted by stocks for the third and fourth quarter of 2020 will be maintained. The empirical section addresses this question.

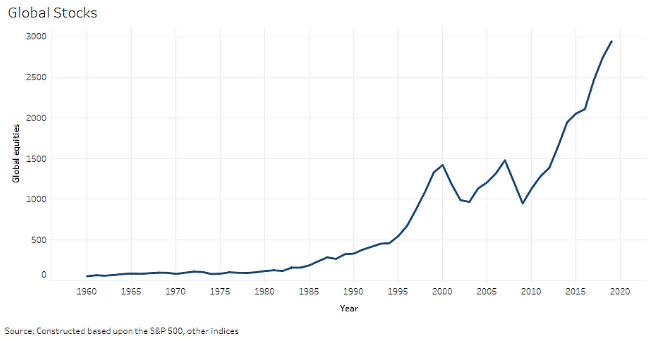

Fig. 7. Global stocks.

III. Method Used

To estimate the effect that COVID-19 already has exerted on GDP, employment, consumer spending and stock markets by the time when the research was conducted, a vector autoregression model was used (VAR). Models using the VAR structure have the advantage of being able to see impacts of each variable on the independent variable and the impacts of the independent variable on the dependent variables. The method is widely used in macroeconomic time-series analyses [6].

A baseline VAR model begins with the following relationship, where the future value of a variable is a function of past values of the variable and contemporaneous and lagged values of other variables that help improve the predictability of the model. In this case, the dependent variable is the performance of global stocks as a function of GDP, employment, and consumer spending, as shown in the following equation. The key insight from VAR models is that they account for the fact that many macroeconomic variables are often not independent of each other. For instance, GDP may help predict future values of stocks, but the stock market also affects GDP. Thus, the equations below show that the two are related.

$$\text{Global stocks}_t = \beta_0^{\text{Global stocks}} + \beta_1^{\text{Global stocks}} \cdot \text{Global stocks}_{t-1} + \beta_2^{\text{GDP}} \cdot \text{GDP}_{t-1} + \beta_3^{\text{Employment}} \cdot \text{Employment}_{t-1} + \beta_4^{\text{Consumer spending}} \cdot \text{Consumer spending}_{t-1} + v_{\text{Global stocks}} \quad (1)$$

$$\text{GDP}_t = \beta_0^{\text{GDP}} + \beta_1^{\text{GDP}} \cdot \text{GDP}_{t-1} + \beta_2^{\text{Global stocks}} \cdot \text{GDP}_{t-1} + \beta_3^{\text{Employment}} \cdot \text{Employment}_{t-1} + \beta_4^{\text{Consumer spending}} \cdot \text{Consumer spending}_{t-1} + v_{\text{GDP}} \quad (2)$$

Similar equations apply for employment and consumer spending, as detailed in the following two equations.

$$\text{Employment}_t = \beta_0^{\text{Employment}} + \beta_1^{\text{Employment}} \cdot \text{Employment}_{t-1} + \beta_2^{\text{GDP}} \cdot \text{GDP}_{t-1} + \beta_3^{\text{Global stocks}} \cdot \text{Global stocks}_{t-1} + \beta_4^{\text{Consumer spending}} \cdot \text{Consumer spending}_{t-1} + v_{\text{Employment}} \quad (3)$$

$$\text{Consumer spending}_t = \beta_0^{\text{Consumer spending}} + \beta_1^{\text{Consumer spending}} \cdot \text{Consumer spending}_{t-1} + \beta_2^{\text{GDP}} \cdot \text{GDP}_{t-1} + \beta_3^{\text{Employment}} \cdot \text{Employment}_{t-1} + \beta_4^{\text{GDP}} \cdot \text{GDP}_{t-1} + v_{\text{Consumer spending}} \quad (4)$$

In this paper, the models include two prior period lags of the independent variables and a constant as the exogenous variable. The modeling was performed in Eviews using the software's baseline or standard VAR model and two other VAR models (simple switching VAR modeling assumptions and vector error correction modeling assumptions). One modeling type that was attempted but would have required adjustments for a near singular matrix was a Bayesian VAR model.

IV. Results

A. Standard VAR

Overall, the standard VAR model has an R-squared of 0.99 for global equities, with an F-statistic of 460 and a Log-likelihood of -340. The complete model reports 36 coefficients. The first numerical column from the left has the results for global equities. The standard errors are reported with parentheses and the t-statistics with brackets. It likely comes as no surprise that past values of global equities help predict future values, although the sign on the second lag of global equities may be surprising. The -0.489 suggests that when equities have a good year, two years before that might have been less than stellar. This type of finding is common in time-series macroeconometrics. Moving to the economic variables, the first reported economic variables are the lags of employment. However, neither the first nor second lag of employment is statistically significant, with t-values of 0.18 and -0.10. This suggests that financial markets often move in directions that are not necessarily consistent with the labor market. Part of this finding might stem from the nature of the two measures. Stock markets generally operate in the world of expectations, where investors attempt to predict future values of stocks before an event actually happens. In contrast, employment is a coincident indicator, moving generally in lock step with the performance of the overall economy. Following the employment results are the results on GDP for the first and second period lags. Notably, only the second lag approaches statistical significance with a t-statistic of 1.87. The coefficient on this is 5.21e-11 (because GDP is measured in trillions of dollars in this model). The positive coefficient on this and the statistical insignificance of the first lag suggests that perhaps GDP is not as good of a predictor of future stock market values as one might think. The last group of reported economic variables is consumer spending. As with employment, consumer spending is not statistically significant at predicting future stock price movements. The statistically insignificant t-statistics for the first and second lags of consumer spending are 0.48 and -1.20.

In addition to the results for global equities, the following Table I also includes results for the other equations in the model. Most of the other economic variables are exhibit no strong statistical predictive power at the 95% confidence level or above. This suggests that perhaps more lags could have been added or a different modeling structure, such as simple multivariate linear regression, would have been a better fit. VAR models are often used in this type of analysis because no variable is truly independent of the other variables. Instead, the relationships generally tend to be circular. In this case, though, the circularity was less transparent.

TABLE I: STANDARD VAR RESULTS

Vector Autoregression Estimates
Date: 05/01/20 Time: 18:54
Sample (adjusted): 3 60
Included observations: 58 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	GLOBAL_EQUITIES	EMPLOYMENT	GDP	CONSUMER_SPENDING
GLOBAL_EQUITIES(-1)	1.376756	-90839.35	-1.40E+09	-3.13E+08
	(0.13836)	(196803.)	(2.9E+09)	(5.3E+08)
	[9.95076]	[-0.46157]	[-0.47760]	[-0.59027]
GLOBAL_EQUITIES(-2)	-0.489106	110364.8	2.62E+09	4.43E+08
	(0.14646)	(208333.)	(3.1E+09)	(5.6E+08)
	[-3.33946]	[0.52975]	[0.84327]	[0.78887]
EMPLOYMENT(-1)	3.79E-08	1.371084	-1011.513	-244.2584
	(2.1E-07)	(0.29238)	(4358.86)	(787.333)
	[0.18426]	[4.68936]	[-0.23206]	[-0.31024]
EMPLOYMENT(-2)	-2.04E-08	-0.376059	1859.798	455.5603
	(2.0E-07)	(0.28187)	(4202.12)	(759.021)
	[-0.10273]	[-1.33416]	[0.44259]	[0.60019]
GDP(-1)	-3.24E-11	-1.14E-05	1.594974	-0.003750
	(2.9E-11)	(4.1E-05)	(0.61175)	(0.11050)
	[-1.12170]	[-0.27689]	[2.60722]	[-0.03394]
GDP(-2)	5.21E-11	3.36E-05	-0.214918	0.102174
	(2.8E-11)	(4.0E-05)	(0.59348)	(0.10720)
	[1.86296]	[0.84512]	[-0.36213]	[0.95312]
CONSUMER_SPENDING(-1)	8.10E-11	6.63E-06	-1.637879	1.228741
	(1.7E-10)	(0.00024)	(3.53463)	(0.63845)
	[0.48601]	[0.02797]	[-0.46338]	[1.92456]
CONSUMER_SPENDING(-2)	-1.93E-10	-0.000167	-1.363569	-0.989719
	(1.6E-10)	(0.00023)	(3.40132)	(0.61438)
	[-1.20237]	[-0.73012]	[-0.40089]	[-1.61093]

Vector Autoregression Estimates
Date: 05/01/20 Time: 18:54
Sample (adjusted): 3 60
Included observations: 58 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	GLOBAL_EQUITIES	EMPLOYMENT	GDP	CONSUMER_SPENDING
C	36.53135	1.46E+08	9.76E+11	2.25E+11
	(64.5816)	(9.2E+07)	(1.4E+12)	(2.5E+11)
	[0.56566]	[1.58779]	[0.71234]	[0.91020]
R-squared	0.986863	0.984990	0.995461	0.992213
Adj. R-squared	0.984718	0.982539	0.994720	0.990942
Sum sq. resids	426007.7	8.62E+17	1.92E+26	6.25E+24
S.E. equation	93.24181	1.33E+08	1.98E+12	3.57E+11
F-statistic	460.1222	401.9369	1343.193	780.4918
Log likelihood	-340.4498	-1162.187	-1719.547	-1620.291
Akaike AIC	12.04999	40.38575	59.60507	56.18244
Schwarz SC	12.36972	40.70547	59.92479	56.50217
Mean dependent	719.8557	2.60E+09	3.01E+13	4.75E+12
S.D. dependent	754.2692	1.00E+09	2.72E+13	3.75E+12

Determinant resid covariance (dof adj.)	2.63E+65
Determinant resid covariance	1.34E+65
Log likelihood	-4678.032
Akaike information criterion	162.5528
Schwarz criterion	163.8317
Number of coefficients	36

B. *Simple Switching VAR*

The switching was modeled as a “simple” switching rather than Markov switching. Table II demonstrates the Markov switching results, which generally confirm the results presented here. Overall, the switching model does produce very good results, with a warning that the singular covariance coefficients are not unique. This, in addition to the non-reporting of standard errors and z-statistics in most cases, confirms that a switching VAR model is not useful for the annual data of this study. It is interesting, though, to compare the coefficients of the simple switching VAR with the standard VAR. Generally, the signs and magnitude of the effects are not dissimilar to the standard VAR results.

TABLE II: SIMPLE SWITCHING VAR

Simple Switching Intercepts VAR Estimates (BFGS / Marquardt steps)
Date: 05/01/20 Time: 18:59
Sample (adjusted): 3 60
Included observations: 58 after adjustments
Number of states: 2
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation
(rng=kn, seed=)
WARNING: Singular covariance - coefficients are not unique
Convergence achieved after 0 iterations
Standard errors in ( ) & z-statistics in [ ]

	GLOBAL_EQUITIES	EMPLOYMENT	GDP	CONSUMER_SPENDING
		Regime 1		
C	36.53135	1.46E+08	9.76E+11	2.25E+11
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
		Regime 2		
C	36.53136	1.46E+08	9.76E+11	2.25E+11
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
		Common		
GLOBAL_EQUITIES(-1)	1.376756	-90839.35	-1.40E+09	-3.13E+08
	(NA)	(NA)	(NA)	(NA)

Simple Switching Intercepts VAR Estimates (BFGS / Marquardt steps)
Date: 05/01/20 Time: 18:59
Sample (adjusted): 3 60
Included observations: 58 after adjustments
Number of states: 2
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation
(rng=kn, seed=)
WARNING: Singular covariance - coefficients are not unique
Convergence achieved after 0 iterations
Standard errors in ( ) & z-statistics in [ ]

	GLOBAL_EQUITIES	**EMPLOYMENT**	**GDP**	**CONSUMER_SPENDING**
	[NA]	[NA]	[NA]	[NA]
GLOBAL_EQUITIES(-2)	-0.489106	110364.8	2.62E+09	4.43E+08
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
EMPLOYMENT(-1)	3.79E-08	1.371084	-1011.513	-244.2584
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
EMPLOYMENT(-2)	-2.04E-08	-0.376059	1859.798	455.5603
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
GDP(-1)	-3.24E-11	-1.14E-05	1.594974	-0.003750
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
GDP(-2)	5.21E-11	3.36E-05	-0.214918	0.102174
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
CONSUMER_SPENDING(-1)	8.10E-11	6.63E-06	-1.637879	1.228741
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
CONSUMER_SPENDING(-2)	-1.93E-10	-0.000167	-1.363569	-0.989719
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
SIGMA-GLOBAL_EQUITIES	7344.961	2.33E+09	6.18E+13	1.15E+13
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
SIGMA-EMPLOYMENT	2.33E+09	1.49E+16	2.01E+20	3.59E+19
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
SIGMA-GDP	6.18E+13	2.01E+20	3.30E+24	5.88E+23
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]
SIGMA-CONSUMER_SPENDING	1.15E+13	3.59E+19	5.88E+23	1.08E+23
	(NA)	(NA)	(NA)	(NA)
	[NA]	[NA]	[NA]	[NA]

Transition Matrix Parameters

Variable	Coefficient	Std. Error	z-Statistic	Prob.
P1-C	0.000000	NA	NA	NA

Determinant resid covariance	1.34E+65
Log likelihood	-4678.032
Akaike info criterion	163.0701
Schwarz criterion	164.8818
Number of coefficients	51

C. Vector Error Correction

The results on the vector error correction generally arrive at the same conclusions as the standard VAR models. There is statistical significance between past values of stock market performance and future values and only weak connections between the economic variables – be it employment, GDP, or consumer spending – and performance of global equities. Although the model produces an adjusted-R2 of 0.449, a

Log-likelihood of -337, and an F-statistic of 4.26, only two of the variables in the model are statistically significant at predicting global equities. That variables are the first- and second-year lags of global equities, with coefficients of 0.74 and -0.57 and t-statistics of 4.51 and -3.12. Overall, a similar conclusion to the standard VAR results.

TABLE III: VECTOR ERROR CORRECTION VAR RESULTS

Vector Error Correction Estimates
Date: 05/01/20 Time: 19:02
Sample (adjusted): 4 60
Included observations: 57 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1			
GLOBAL_EQUITIES(-1)	1.000000			
EMPLOYMENT(-1)	3.36E-07			
	(1.5E-07)			
	[2.22642]			
GDP(-1)	-4.04E-12			
	(4.3E-11)			
	[-0.09432]			
CONSUMER_SPENDING(-1)	-1.58E-10			
	(3.3E-10)			
	[-0.47522]			
C	-701.3064			
Error Correction:	**D(GLOBAL_EQUITIES)**	**D(EMPLOYMENT)**	**D(GDP)**	**D(CONSUMER_SPENDING)**
CointEq1	0.096182	147848.5	4.12E+09	6.81E+08
	(0.05979)	(64709.8)	(8.6E+08)	(1.4E+08)
	[1.60858]	[2.28480]	[4.79233]	[4.75032]
D(GLOBAL_EQUITIES(-1))	0.744287	229368.9	3.07E+09	6.74E+08
	(0.16493)	(178493.)	(2.4E+09)	(4.0E+08)
	[4.51272]	[1.28503]	[1.29344]	[1.70516]
D(GLOBAL_EQUITIES(-2))	-0.573083	-849029.2	-1.55E+10	-2.93E+09
	(0.18344)	(198522.)	(2.6E+09)	(4.4E+08)
	[-3.12413]	[-4.27676]	[-5.85740]	[-6.66196]
D(EMPLOYMENT(-1))	1.20E-07	0.991493	5858.662	1118.006
	(2.6E-07)	(0.28287)	(3760.34)	(626.626)
	[0.45732]	[3.50509]	[1.55801]	[1.78417]
D(EMPLOYMENT(-2))	-2.26E-07	-0.563838	-5071.933	-1002.235
	(2.4E-07)	(0.26417)	(3511.73)	(585.197)
	[-0.92570]	[-2.13437]	[-1.44428]	[-1.71264]
D(GDP(-1))	-4.63E-11	-0.000116	-1.074544	-0.368017
	(4.1E-11)	(4.4E-05)	(0.59086)	(0.09846)
	[-1.12634]	[-2.60743]	[-1.81861]	[-3.73768]
D(GDP(-2))	3.35E-11	9.25E-05	1.412043	0.325526
	(3.8E-11)	(4.2E-05)	(0.55187)	(0.09196)
	[0.87423]	[2.22890]	[2.55866]	[3.53972]
D(CONSUMER_SPENDING(-1))	1.11E-10	0.000334	4.670947	1.673346
	(2.2E-10)	(0.00023)	(3.10431)	(0.51730)
	[0.51264]	[1.43228]	[1.50467]	[3.23474]
D(CONSUMER_SPENDING(-2))	-4.03E-11	-0.000276	-4.956947	-1.253888
	(2.0E-10)	(0.00022)	(2.93792)	(0.48958)
	[-0.19721]	[-1.24977]	[-1.68723]	[-2.56116]
C	52.24278	84854902	1.64E+12	2.88E+11
	(21.0174)	(2.3E+07)	(3.0E+11)	(5.0E+10)
	[2.48569]	[3.73060]	[5.43311]	[5.71373]
R-squared	0.449142	0.453020	0.628670	0.652080
Adj. R-squared	0.343659	0.348280	0.557564	0.585457
Sum sq. resids	459586.5	5.38E+17	9.51E+25	2.64E+24
S.E. equation	98.88598	1.07E+08	1.42E+12	2.37E+11
F-statistic	4.257939	4.325159	8.841339	9.787616
Log likelihood	-337.2379	-1129.226	-1670.443	-1568.304
Akaike AIC	12.18379	39.97285	58.96290	55.37907
Schwarz SC	12.54222	40.33128	59.32133	55.73750
Mean dependent	50.45624	57361687	1.56E+12	2.13E+11
S.D. dependent	122.0590	1.33E+08	2.14E+12	3.68E+11
Determinant resid covariance (dof adj.)		1.43E+65		
Determinant resid covariance		6.62E+64		
Log likelihood		-4577.300		
Akaike information criterion		162.1509		
Schwarz criterion		163.7280		
Number of coefficients		44		

D. Comparing the Impulse Response Functions

It is evident from the data presented in this section demonstrates that the economic variables of significance to the study, the GDP and stock return values adopt a declining trend following the outbreak of the virus. Consequently, it is evident from the two models that the global Coronavirus outbreak, to a large extent, has contributed to declining global economic performance.

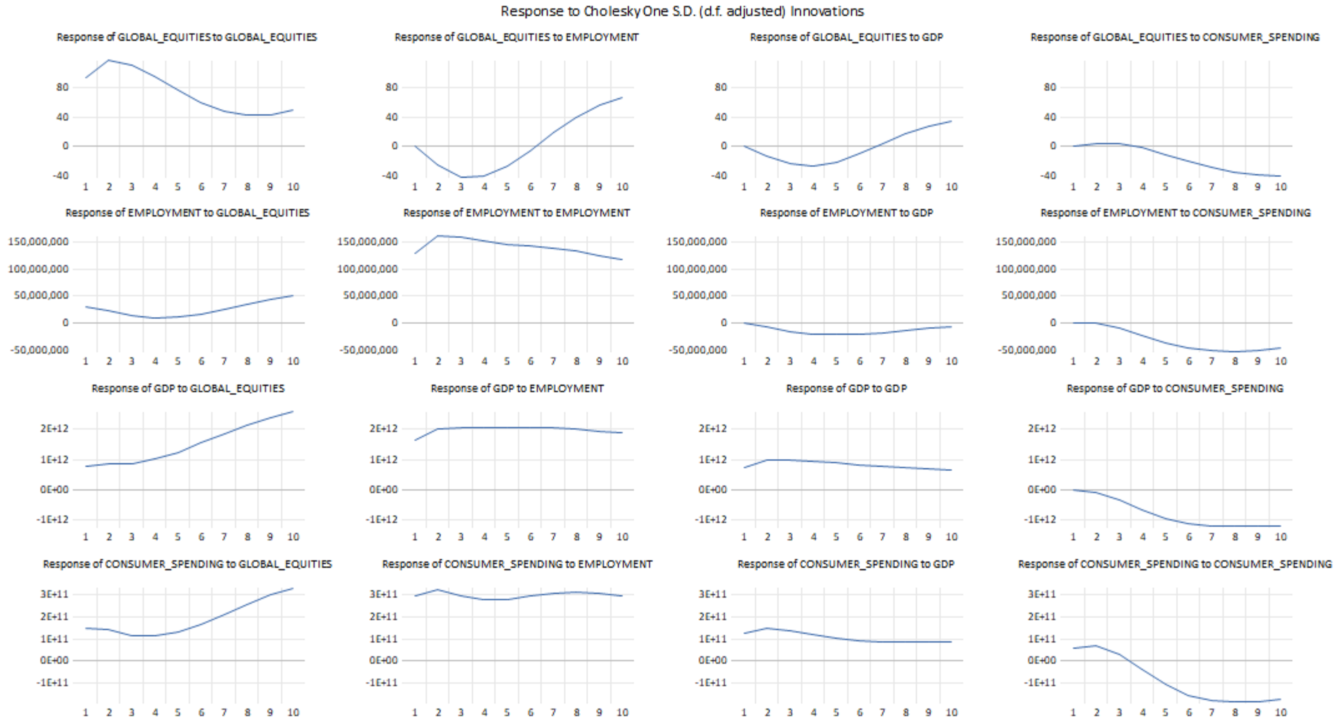

Fig. 8. Standard VAR impulse response function.

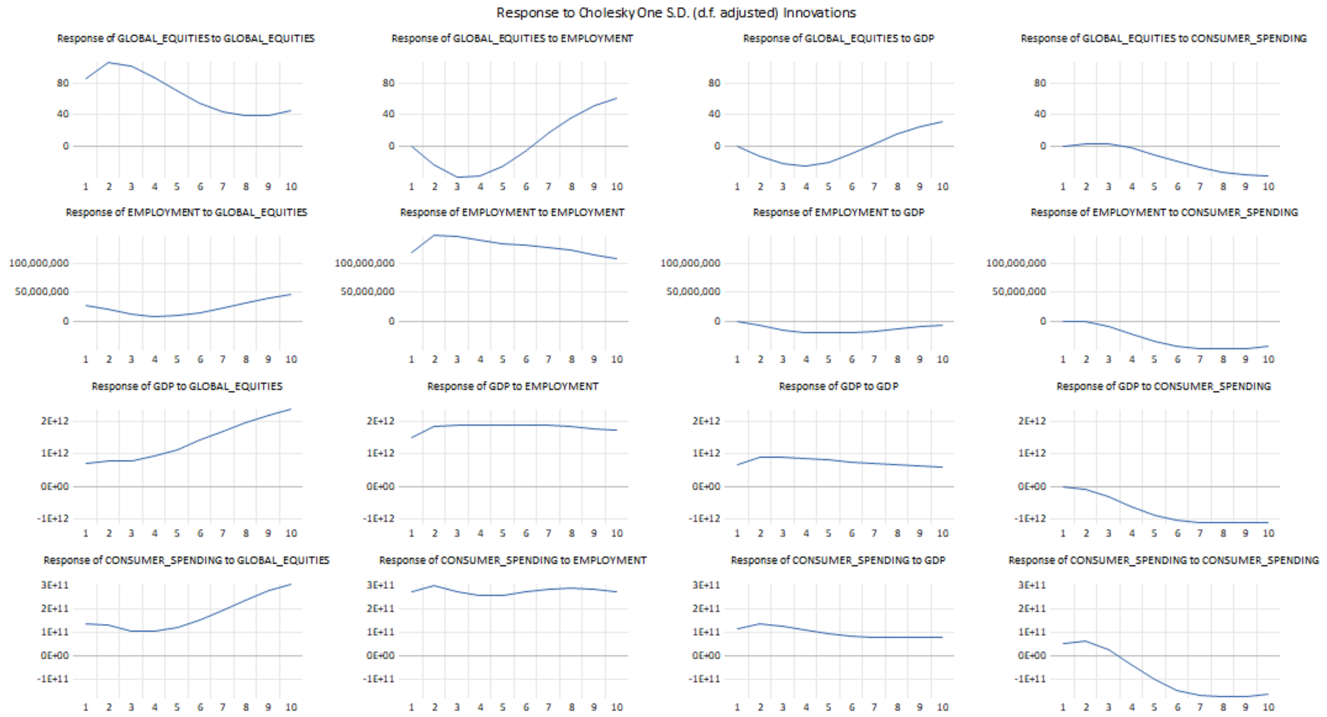

Fig. 9. Switching VAR impulse response function.

V. Conclusions

Overall, the vector autoregression models presented in this paper provide guidance and useful insight into stock markets and the global economy in a time of heightened uncertainty. In attempting to connect the performance of global equity markets with the performance of employment, GDP, and consumer spending, the relationship is not as tight as one might expect. Perhaps because global equities are leading indicators of economic activity and employment, GDP, and consumer spending are coincident indicators, none of the VAR models presented provided strong empirical evidence of a lasting short-term relationship when using annual data back to 1960 and attempting to infer what the effect these economic measures may have on global stock market performance for 2020. Suffice it to say that global markets and the economy responded to COVID-19 with lightning fast speed, causing widespread unemployment, lower consumer spending, and global equity markets down 40%. Should the COVID-19 continue to have a prolonged effect on "lockdown" behavior, the global economy may continue to sputter, and global equity markets could turn south again. With this acknowledged, the interesting finding from this study was that global equity markets are not as tightly intertwined with economic activity, with none of the economic variables – employment, GDP, or consumer spending – statistically significant in predicting changes in global equities.

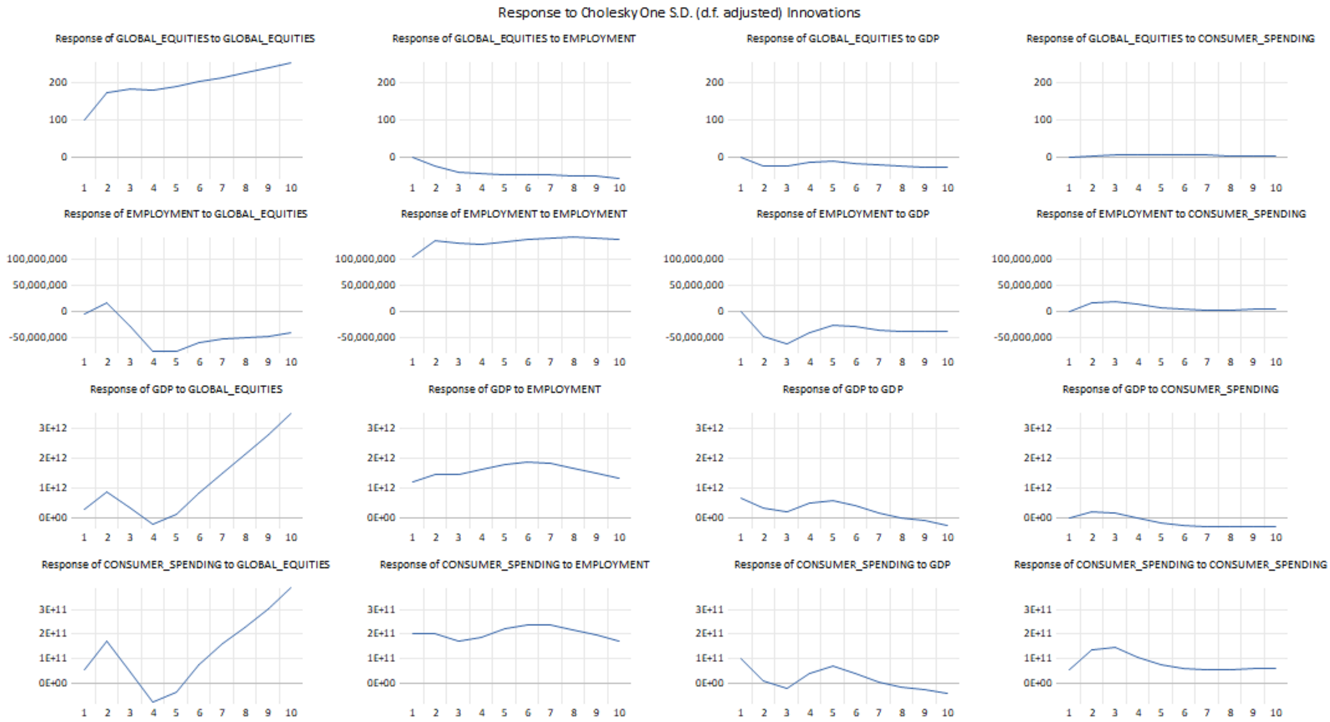

Fig. 10. Vector error correction impulse response function.

Conflict of Interest

The author declares no conflict of interest.

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Yijia Ren was born on May 13, 1992 in Hunan Province, China. From 2011 to 2015, She studied accounting at the Central South University of Forestry and Technology and got her bachelor's degree in June 2015. From 2018 to 2020, she studied financial engineering at the University of Southern California and got her master's degree in May 2020.

She participated in the research on the variability of Google stock price based on historical simulation model in R from January 2019 to March 2019.

Ms. Ren worked as an accountant in Hunan T-Center Group from February 2015 to January 2018.