EFFECT OF COVID-19 ON STOCK PRICES

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May 14, 2022

Abstract

The purpose of this study was to dissect the impact of COVID-19 cases on stock price of the largest public companies by market capitalization in each of the 11 Global Industry Classification Standard (GICS) sectors, from March 9th, 2020, until December 27th, 2021. This topic is so interesting considering the behavior of the S&P 500 index for example, which rose 58.50% while COVID-19 cases soared well over one hundred thousand new cases per week throughout the same period. Research done on a pandemic's effect on stock markets have had the opposite response, at least for a year or so until the markets stabilize, including the Spanish Flu (1918-1920), Asian Flu (1957-1958), and more recently the SARS virus (2003). This study was conducted using panel regression analysis, and using observations gathered on a weekly occurrence. This study concluded that there is a highly significant positive relationship between the closing price of the 11 companies with new weekly COVID-19 cases, meaning that every time there was an increase in COVID-19 cases by 1%, the closing price of the 11 companies would increase by 1.9%. The outcome can be explained by an increased number of people having time to day trade due to layoffs or working from home, COVID-19-related stimulus packages offering the average American more funds to invest, or the most likely – investors looking past the catastrophic event to eventually return to normality as the reason to invest.

Key words: COVID-19, Pandemic, Stock Market, Stock Price

Introduction

Global pandemics throughout history have caused catastrophic levels of sickness and death across the world, and no different was the COVID-19 pandemic that leveled the world economy during a period of all-time highs and record-breaking performances across sectors. Firstly, for a disease to be identified as a pandemic as opposed to an epidemic, it must spread across countries and continents, which we saw start in February 2020 in Wuhan, China and spread globally over the next 1-2 years. Though COVID-19 was classified similarly to other pandemics, what made this virus so different was the mortality rate, contagion rate, and stock market response. Like other pandemics, COVID-19 took a large toll on the market around April 1, 2020, after schools, workplaces and especially restaurants went virtual or prioritized social distancing after seeing some of the first cases in the United States. Though, most of the population was hopeful – there were a few studies that estimated the number of COVID-19 cases that occurred between 3°C and 17°C degrees were greater than cases that occurred outside of that range of temperatures, but it couldn't be proven that the warm weather the summer would bring would help decrease cases (Bukhari, Qasim, et al.). After the initial outbreak and stock market crash, something unexpected happened – the market rebounded and didn't stop expanding minus

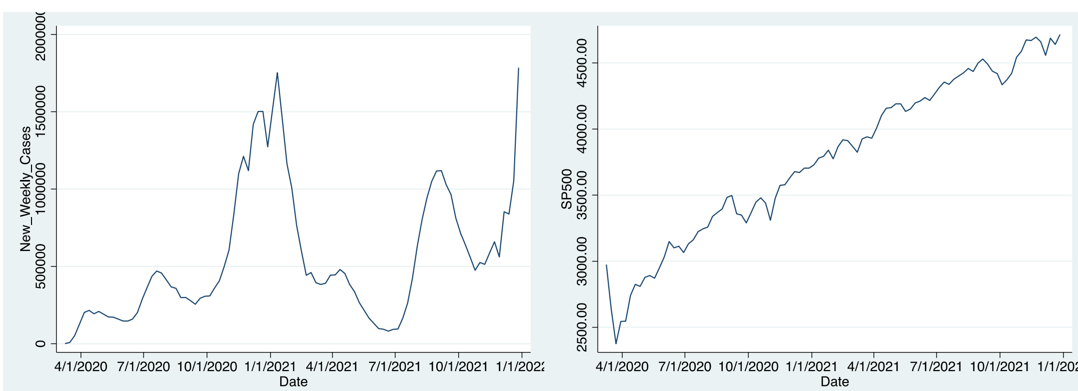

Figure 1

a few dips and drops along the way, resulting in the S&P 500 growing from 2400 after the initial crash, to 4700 by December 2021. This rapid market expansion occurred synonymously with the exponential growth of global COVID-19 cases, which is what was such an interesting relationship to investigate.

Most of the literature surrounding COVID-19 doesn't look at the specific macroeconomic variables that are regarded in this study, which is just one of the ways in which this study is contributing to the field. Over the course of this paper, you'll see how different variables with weekly observations are correlated with the adjusted closing price of the 11 companies that will be revealed in the methodology section, but up next is a summary of the literature in this field.

Literature Review

There are numerous academic articles published during and after the brunt of the COVID-19 pandemic, covering lots of different topics such as what temperature ranges most COVID-19 cases were being recorded in (Bukhari et al., 2020), communities of color having a higher risk for health and economic challenges during COVID-19 (Garfield et al., 2020) as well as scientific articles like aerosol and surface stability of SARS-COV-2 as compared with SARS-COV-1 (Doremalen et al., 2020). Though, the academic articles that were most relevant to this study were those that could be grouped into two distinct categories: those analyzing the market's reaction to the COVID-19 pandemic, and those focused on measuring stock market performance over the period. This study wasn't so much concerned with stock market performance (meaning cumulative or inflation-adjusted returns) as it was with general price appreciation of the 11 leaders of each sector – while most other pieces of literature covered larger swaths of the market with sector-specific ETF's or the top 100-500 stocks in the most relevant stock exchange to the author(s).

COVID-19 affected every country across the globe, and it can be expected that each country had its own unique way of handling the outbreak, vaccinations, lockdowns, quarantine protocol and more. What also varied across countries was the adverse effects of the virus, specifically among countries with different levels of freedom. This was expanded upon in a study done by Orhan Erdem (Erdem, 2020) who performed a panel regression analysis of 75 countries in 2020, each with their respective stock exchange and the CBOE Volatility Index (VIX) as dependent variables, with Freedom Score and country-specific COVID-19 data as the independent variables. This study proved that countries with more freedom were subject to less detrimental effects of COVID-19 (based on deaths and other factors), as well as less severe market declines than those who lived in countries with less freedom.

A major part of the battle at the start of the COVID-19 pandemic was trying to estimate the potential impact of a virus of this scale on the economy, as well as considering the virus' contagion and mortality rates to encourage governments and municipalities to engage in widespread (semi) mandatory lockdowns. It didn't necessarily come just in time, but there was a study conducted in March 2020 (Barro, Robert et al.) that detailed the history of pandemics including death tolls and economic costs to extrapolate past reactions of viruses to the new COVID-19 outbreak. This study tells us that influenza from 1918-1920 serves as the worst-case scenario for a similar pandemic, with 40 million deaths (2.1% death rate at the time) which implied 'flu-generated' economic declines of 6% for GDP, and 8% for consumption from the start of 1918 to the finish in 1920 (Barro, Robert et al.). Considering that same death rate and applying it to the current global population, 2.1% is roughly 150 million deaths which Barro believed would cause a similar economic event as to what occurred in the 2008-2009 Great Financial Crisis. More notably, some evidence was found to suggest that ‘higher flu death rates decreased real returns on stocks and especially short-term notes’ (Barro).

Measuring and predicting an economic event is one thing, but explaining why requires a much more in-depth analysis. Throughout the pandemic it was anyone’s guess as to which industry or group of industries could wait out the storm, minimize losses or even benefit due to a previously developed pandemic contingency plan. So, a study was conducted in November 2021to show which industries had better reactions to COVID-19 announcements in a period of 10 days before and after a COVID-19 related announcement. This study considered each industry in the IPSA (Selective Stock Price Index), and their respective abnormal returns along with the cumulative abnormal returns to explain why certain industries in Chile performed better than others before and after COVID-19 announcements. This result should not come as a surprise, but the study concluded that the “IPSA reacted inefficiently to the COVID-19 outbreak, which resulted in many strongly negative abnormal returns for most sectors besides utilities” (González et al.). This proves that the statement, the tide raises/lowers all ships is also true in the case of industries reactions in the Chilean markets, but that there are always some ships that are better built for catastrophic scenarios – the same story with industries and systematic events.

An organization’s business continuity strategy plays a key role in adapting to natural disasters, acts of terrorism, an internal network failure and other external threats to normal business activity. Though, one external event that very few companies expected to occur was a global pandemic that would bear its mark on the business world forever, whether the company was public, private, big, or small. A public company reports the risk factors to their business activities in Item 1A of their annual reports, and a study done by Jordan Schoenfeld seeks out companies in the S&P 500 that elected to list ‘Pandemic’ as a risk factor, and what effect (if any) that had on their performance during COVID-19 (Schoenfeld, 2020). This study found that companies that neglected to mention COVID-19 as a risk factor made up over 56% of all the companies in the S&P 500, and those same companies experienced a mean decrease in returns of 32%, but so did the companies that included 'Pandemic' as a risk factor. This means that investors couldn't have chosen which stocks would be exposed to the COVID-19 pandemic based off SEC mandated business risk factors alone.

As the COVID-19 pandemic evolved, so did the investors that now had more time than ever to day trade and speculate with some extra liquidity thanks to the expansionary monetary policy employed by the FED. One may think that any announcement by a company about COVID-19 would result in a decrease in stock price, but according to (Ramelli et al., 2020) it had the opposite effect. This paper found that firms who publicly mentioned COVID-19 had higher average cumulative returns over the period of December 2018 – April 2020, being most mentioned by companies with international exposure. While normal stock price appreciation can be all that an investor needs to realize growth in their portfolio, there's another factor that can boost their return – dividends. Dividend behavior fluctuates with market activity as well, if a certain company has a bad quarter and does not feel they have enough left over to give to investors, that will likely lower its stock price. That's exactly what was found to happen in a study that inspected dividend growth rates in response to changes in the S&P 500, EuroStoxx50, Nikkei225, U.S. Treasuries (30 year), German Bunds, and Japanese treasuries. This study concluded that while long-term dividend growth increased from January 2020 – June 2020 – which the study said was aided by federal stimulus - short-term dividend growth declined in all geographies over that same period.

Methodology

This study is based on data collected from 11 companies, from March 9, 2020, to December 27, 2021. The companies are Apple, BHP, Exxon Mobil, UnitedHealth, NextEra Energy, Prologis, Proctor & Gamble, Amazon, Google, and JP Morgan (Figure 2).

Figure 2

GICS Sector	*Energy*	*Materials*	*Industrial.*	*Cons. Disc.*	*Cons. Stap.*	*Health Care*
Company	Exxon Mobil	BHP	UPS	Amazon	P&G	UNH
GICS Sector	Financials	Info. Tech.	Comm. Svcs	Utilities	Real Estate	
Company	J.P. Morgan	Google	Apple	NextEra	ProLogis	

In this study, the dependent variable is the adjusted closing price taken weekly for each company. The main independent variable is new weekly COVID-19 cases, with additional independent variables that include the Federal Funds Rate (FFR), the Initial Claims Index (ICSA), the Weekly Economic Index (econ_index), and the CBOE Volatility Index (VIX). Weekly COVID-19 cases were created for the purpose of this study by taking the sum of the daily

Figure 3

Variables	Definition	Frequency of Data	Data Source	Hypothesized sign of coefficient
Ln_Close (Dependent variable)	Adjusted closing price of all 11 leaders of GICS Sectors	Weekly	Yahoo Finance	N/A
Ln_Cases	Amount of new weekly COVID-19 cases	--	CDC Covid-19 tracker	-
Econ_Index	Weekly economic index - made up of a bunch of smaller indicators	--	FRED Database	+
Ln_ICSA	Initial unemployment claims	--	FRED Database	-
FFR	Federal Funds Rate	--	FRED Database	-
VIX	CBOE Volatility Index	--	Yahoo Finance	-

cases in a week and measuring as of the end of that week along with the rest of the data.

The rest of the variables are standard and come from the sources listed above that consist of YahooFinance, CDC Covid-19 Tracker and the Federal Reserve Bank of St. Louis (Figure 3).

As for the hypothesized signs of the coefficients, it had initially been hypothesized that an increase in COVID-19 would depress investor behavior and encourage selling off, meaning a negative coefficient on new COVID-19 cases. Next, if the Weekly Economic Index increased (which contains a basket of other economic indicators), it can be reliably assumed that it would have a positive effect on closing price. Next, the Initial Claims variable records unemployment claims which are known to depress financial markets as well as job markets overall, hence the negative expected sign. Additionally, an increase in the Federal Funds Rate is usually associated with broader stock market declines, most notably what can be seen occurring at this very moment in time with the FED implementing Quantitative Tightening (QT) methods, so a negative coefficient only makes sense. Finally, an increase in stock market volatility can be scary to investors, which may cause them to either sell off, or not buy and wait for a less volatile time to invest – this explains the negative expected sign for VIX. Additionally, the reason that larger macroeconomic variables like GDP, Unemployment, industrial production, inflation, or consumer sentiment had to be excluded was because they are either published quarterly or monthly, which cannot be easily adapted to weekly data without having an estimation error, however small.

Given the hypothesized signs of the coefficients of each variable, the model specified for this study is as follows:

$$Ln\_close_{it} = \beta_0 - \ln\_Cases\beta_T + Econ\_Index_{it}\beta_T - \ln\ \_ICSA_{it}\beta_T - FFR_{it}\beta_T - VIX_{it}\beta_T + \in$$

This is a hybrid log-log model, with logs only being placed on variables to reduce the wide range between minimum and maximum values. It was especially necessary for New Weekly

COVID-19 cases, which grew exponentially over the period. When logs were placed on the remaining variables, it did not help results, hence why no change was made. This resulted in the best model according to initial regressions done in the early stages of this study. Throughout this study, a Hausman test was done to select either the fixed or random effects model, with tests for heteroskedasticity, serial correlation, and multicollinearity performed to understand data quality and any concerns for making assumptions.

Figure 4

Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
ln_close	overall	5.258634	1.328354	3.355319	8.221301	N = 1095
	between		1.373689	3.824373	8.032322	n = 11
	within		.2177324	4.523679	5.707206	T = 95
ln_new_cases	overall	12.84005	1.131489	6.028278	14.39494	N = 1095
	between		0	12.84005	12.84005	n = 11
	within		1.131489	6.028278	14.39494	T = 95
ln_ICSA	overall	13.43781	.7797684	12.1442	15.6318	N = 1095
	between		0	13.43781	13.43781	n = 11
	within		.7797684	12.1442	15.6318	T = 95
VIX	overall	24.40568	9.609691	15.07	66.04	N = 1095
	between		3.73e-15	24.40568	24.40568	n = 11
	within		9.609691	15.07	66.04	T = 95
FFR	overall	.1015038	.1436609	.0471429	1.161429	N = 1095
	between		0	.1015038	.1015038	n = 11
	within		.1436609	.0471429	1.161429	T = 95
Econ_Index	overall	1.392737	6.086841	-9.48	11.21	N = 1095
	between		0	1.392737	1.392737	n = 11
	within		6.086841	-9.48	11.21	T = 95

The descriptive statistics of the dataset are shown above in Figure 4. What can be gleaned from this information is that thanks to the logs on appropriate variables there is little variation between the minimum and maximum values, much less than without. There are 1095 observations in total, with 95 weekly observations for each of the 11 companies included in this study (Figure 1). Additionally, there is an extremely small standard deviation value in the "Between" column for VIX, which should not occur since VIX should not vary between companies – it's a market-wide volatility measure, not company-specific. This could be explained by a data ingestion issue, but when investigating further none could be found. Most variables have similar standard deviations, besides VIX and Econ_Index which are many times higher than the other independent variables.

Figure 5

Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) ln_close	1.000					
(2) ln_new_cases	0.072**	1.000				
(3) ln_ICSA	-0.115***	-0.119***	1.000			
(4) VIX	-0.118***	-0.588***	0.473***	1.000		
(5) FFR	-0.050	-0.688***	-0.215***	0.583***	1.000	
(6) Econ_Index	0.120***	0.108***	-0.802***	-0.540***	-0.004	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 5 contains the covariance matrices for the 1%, 5%, and 10% significance levels denoted by the number of asterisks associated with each (Figure 5). There is particularly high correlation between the Economic Index and ICSA since the economic index contains the ICSA as one of the weekly economic indicators in its basket. The other notable correlation is between weekly COVID-19 cases and the adjusted closing price, which is a positive 7% - the opposite of what this study hypothesized.

Figure 6 below shows initial regression results for the fixed effect model, Figure 7 shows initial regression results for random effect, and Figure 8 shows a Hausman test to decide between the two models.

Figure 6

Regression results

ln_close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln_cases	.019	.005	3.91	0	.009	.028	***
ln_icsa	-.118	.01	-12.01	0	-.137	-.098	***
vix	-.004	.001	-6.22	0	-.006	-.003	***
ffr	-.332	.049	-6.74	0	-.428	-.235	***
econ	.01	.001	9.54	0	.008	.012	***
Constant	6.722	.165	40.70	0	6.398	7.046	***

Mean dependent var	5.259	SD dependent var	1.328
R-squared	0.743	Number of obs	1045
F-test	596.466	Prob > F	0.000
Akaike crit. (AIC)	-1631.360	Bayesian crit. (BIC)	-1601.649

*** $p<.01$, ** $p<.05$, * $p<.1$

From what can be seen from the fixed effect model, there is an R^2 value of 74.3% - not bad! Additionally, the P-values for each of the variables is zero, which means each variable is statistically significant at the 10%, 5% and 1% level in the bounds of this dataset. What is even more surprising is the positive coefficient of ln_cases, something that was discussed briefly in Figure 5. This disproves the initial hypothesized sign of coefficients, and certainly was not expected in this study. This means that for every 1% increase in weekly COVID-19 cases, the adjusted closing price will increase by 1.9%. The rest of the coefficient's signs were as expected, with very little standard errors and relatively high t-values. This means the estimated regression model is as follows:

Ln_close = 6.72 + .019(Ln_Cases) - .004(VIX) - .332(FFR) + .010(Econ_Index) - .118(ln_ICSA)

Figure 7

Regression results

ln_close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln_cases	.019	.005	3.91	0	.009	.028	***
ln_icsa	-.118	.01	-12.01	0	-.137	-.098	***
vix	-.004	.001	-6.22	0	-.006	-.003	***
ffr	-.332	.049	-6.74	0	-.428	-.235	***
econ	.01	.001	9.54	0	.008	.012	***
Constant	6.722	.446	15.08	0	5.848	7.596	***

Mean dependent var	5.259	SD dependent var	1.328
Overall r-squared	0.020	Number of obs	1045
Chi-square	2982.331	Prob > chi2	0.000
R-squared within	0.000	R-squared between	0.000

**** p<.01, ** p<.05, * p<.1*

From what can be seen from the random effects model, there is an overall R^2 value of 2%, not so great in comparison to the fixed effect model. Though, notice that the coefficients do not change from fixed effect to random effect. This can be seen further in the Hausman test results in Figure 8.

Figure 8

Hausman (1978) specification test

	Coef.
Chi-square test value	0
P-value	1

	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
ln_new_cases	.0187	.0187	3.68e-16	.
ln_ICSA	-.1176725	-.1176725	2.32e-15	.
VIX	-.0042166	-.0042166	-3.82e-17	.
FFR	-.3316666	-.3316666	6.72e-15	.
Econ_Index	.0100456	.0100456	2.12e-16	.

b = Consistent under H0 and Ha; obtained from **xtreg.**
B = Inconsistent under Ha, efficient under H0; obtained from **xtreg.**

These inconclusive results from the Hausman test resulted in the fixed effect model being chosen as the coefficients, statistically significant variables and low standard errors are the same between the two models – with the fixed effect model having a much higher R^2.

Next up was testing for heteroskedasticity (Figure 9), serial correlation (Figure 10), and multicollinearity (Figure 11).

Figure 9

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (11)  =     292.22
Prob>chi2 =      0.0000
```

Regression results

ln_close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln_new_cases	.019	.009	2.01	.072	-.002	.039	*
ln_ICSA	-.118	.028	-4.28	.002	-.179	-.056	***
VIX	-.004	.001	-3.19	.01	-.007	-.001	***
FFR	-.332	.09	-3.67	.004	-.533	-.13	***
Econ_Index	.01	.003	3.39	.007	.003	.017	***
Constant	6.722	.374	17.97	0	5.889	7.556	***

Mean dependent var	5.259	SD dependent var	1.328
R-squared	0.743	Number of obs	1045
F-test	58.225	Prob > F	0.000
Akaike crit. (AIC)	-1633.360	Bayesian crit. (BIC)	-1608.601

*** *p*<.01, ** *p*<.05, * *p*<.1

As can be seen from the xttest3 results on the upper left, heteroskedasticity does in fact exist in the data and once this was discovered, the vce (robust) function was ran to show robust any specification error. There were a few changes to the p-values of each of the variables with *most* not being significant enough to make the variable less statistically significant besides

COVID-19 cases which fell from being significant at the 1%, 5% & 10% level, to only 5% & 10%. Also, the standard errors increased, but that was meant to happen with the use of this test.

Next up is to see whether serial correlation is present in the dataset in Figure 10.

Figure 10

Linear regression

Number of obs = 1,034
F (5, 10) = 74.11
Prob > F = 0.0000
R-squared = 0.2655
Root MSE = .03856

(Std. err. adjusted for 11 clusters in Company_ID)

D.ln_close	Coefficient	Robust S.E.	t	P>t	95% Confidence Interval	
ln_new_cases D1.	-0.037	0.007	-5.210	0.000	-0.052	-0.021
Ln_ICSA D1.	-0.054	0.010	-5.420	0.000	-0.077	-0.032
VIX D1.	-0.004	0.000	-13.650	0.000	-0.005	-0.003
FFR D1.	-0.377	0.044	-8.560	0.000	-0.475	-0.279
Econ_Index D1.	0.003	0.001	2.460	0.034	0.000	0.006

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F (1, 10) = 109.035
Prob > F = 0.0000

According to Figure 10 above, there is in fact serial correlation since one must reject the null hypothesis that there is no first order autocorrelation because the Prob > F is less than our acceptance level of 0.05. But it is not severe serial correlation because the robust standard errors are very small. Finally, the dataset needs to be tested for multicollinearity.

Figure 11

Variance inflation factor

	VIF	1/VIF
ln ICSA	4.943	.202
FFR	4.229	.236
VIX	3.59	.279
Econ Index	3.477	.288
ln new cases	2.475	.404
Mean VIF	3.743	

According to Figure 11 above, the correlation among the variables in this study is moderately correlated, since it is between 1 and 5. This means that for each one of the variables, the variance of the regression coefficients is not very inflated due to multicollinearity being present in the model.

Below, there will be a robustness check using different empirical models including linear, left-hand semi-log, right-hand semi-log, and a double log model – all of which were not chosen as the empirical model of choice but will be shown here to explain why the final model that was chosen was superior.

Figure 12.1-12.4

Regression results

Adj_Close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln_new_cases	14.026	7.71	1.82	.069	-1.122	29.174	*
ln_ICSA	-99.424	21.297	-4.67	0	-141.266	-57.583	***
ln_VIX	-123.044	42.903	-2.87	.004	-207.337	-38.751	***
ln_FFR	-50.523	25.992	-1.94	.052	-101.59	.544	*
ln_ECON	1.111	9.096	0.12	.903	-16.76	18.982	
Constant	1990.117	369.415	5.39	0	1264.324	2715.909	***

Mean dependent var	654.070	SD dependent var	1099.003
R-squared	0.208	Number of obs	517
F-test	26.381	Prob > F	0.000
Akaike crit. (AIC)	6647.184	Bayesian crit. (BIC)	6672.673

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

ln_close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
New_Cases	0	0	6.49	0	0	0	***
VIX	-.005	.001	-6.86	0	-.007	-.004	***
FFR	-.257	.041	-6.24	0	-.338	-.176	***
Econ_Index	.017	.001	20.68	0	.016	.019	***
ICSA	0	0	-6.51	0	0	0	***
Constant	5.39	.017	320.27	0	5.357	5.423	***

Mean dependent var	5.259	SD dependent var	1.328
R-squared	0.716	Number of obs	1045
F-test	518.492	Prob > F	0.000
Akaike crit. (AIC)	-1524.513	Bayesian crit. (BIC)	-1494.802

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

ln_close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
ln_new_cases	.015	.005	3.23	.001	.006	.024	***
ln_ICSA	-.153	.013	-12.07	0	-.178	-.128	***
ln_VIX	-.203	.025	-7.95	0	-.253	-.153	***
ln_FFR	-.135	.015	-8.75	0	-.165	-.105	***
ln_ECON	-.004	.005	-0.68	.497	-.014	.007	
Constant	7.442	.219	33.93	0	7.011	7.873	***

Mean dependent var	5.395	SD dependent var	1.326
R-squared	0.704	Number of obs	517
F-test	238.609	Prob > F	0.000
Akaike crit. (AIC)	-1034.395	Bayesian crit. (BIC)	-1008.907

*** *p<.01*, ** *p<.05*, * *p<.1*

Regression results

Adj_Close	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
New_Cases	0	0	1.57	.116	0	0	
VIX	-2.578	1.294	-1.99	.047	-5.118	-.038	**
FFR	-144.508	69.779	-2.07	.039	-281.434	-7.583	**
Econ_Index	9.277	1.405	6.60	0	6.519	12.034	***
ICSA	0	0	-2.45	.015	0	0	**
Constant	650.765	28.517	22.82	0	594.806	706.723	***

Mean dependent var	578.017	SD dependent var	1000.562
R-squared	0.203	Number of obs	1045
F-test	52.400	Prob > F	0.000
Akaike crit. (AIC)	14015.024	Bayesian crit. (BIC)	14044.735

*** *p<.01*, ** *p<.05*, * *p<.1*

The linear form was not chosen since the coefficients for New_Cases and the ICSA were both zero, along with the fact that the R^2 was very low at 20%. The double log form was not chosen since the R^2 on the hybrid empirical model that has been previously specified was higher. This was initially the model of choice, that is until experimentation was done with putting logs on only a few independent variables after criticisms after the first presentation. The left-hand semi-log form was not chosen for the same reason the linear form was thrown out – the coefficients for New_Cases and ICSA were zero, with a strong R^2 and slightly higher standard errors. Finally, the right-hand semi-log form was not chosen because the R^2 was quite low compared to the other models, and certain variables like the FFR and New_Cases were no longer significant at the 1% level. Not only that, but the coefficients and standard errors were much higher.

Discussion

The empirical results show that there is a small positive relationship between adjusted closing price of the 11 companies in the study, and the weekly COVID-19 cases during the period. It has been mentioned before some of the potential reasons for this which can be a few things. Firstly, the FED began quantitative easing (QE) measures on March 15, 2020 – and from that point on economic stimulus began flooding into financial markets. This formally started with the CARES Act on March 26, 2020 which 'provided $2T in aid to hospitals, small businesses, and state and local governments' (CDC Museum Covid-19 Timeline) but continued throughout the rest of the year in various forms. Eviction moratoriums, stimulus payments, student loan payment pauses, the Paycheck Protection Program (PPP) and other Small Business Administration loans, and the purchase of corporate junk bonds by the FED were just some of the ways in which the government banded together to use the full force of monetary and fiscal policy to ease the public. It can be understood then why the public began to feel more comfortable in the middle of an unprecedented moment in history and jumped on board with the Federal Reserve – "if the FED is buying, I should be too!". It cannot be determined whether the positive relationship shown in the results is from institutional or retail investors or even a combination of the two. Regardless, would be an interesting study to conduct. Likely it was both, with retail investors feeling more confident having the government behind them, giving the markets fuel to start again. The FED was buying so many treasuries, mortgage-backed securities, and other financial instruments that keep the world running, which was signaling to investors that things were going to be OK. This study concluded that with an increase in COVID-19 cases of 1%, that the adjusted closing price would increase by 1.9% ceteris paribus (other things equal), with every variable in the study being statistically significant at the 1%, 5%, and 10% levels to back up this surprising result.

Conclusion

The COVID-19 pandemic rocked the global economy on an unprecedented scale, with the long-term effects to be felt for years to come – with jobs, loved ones, and the once traditional in-person work environment lost to a virus more malevolent than most have witnessed in their lifetime. Those invested in the financial markets benefited from the unexpected positive relationship between COVID-19 cases and adjusted closing stock price. As citizens continue to grapple with the economic loss and companies struggle to attract and retain employees in a post-COVID world, a recession has begun. For all the QE that was provided in 2020 and 2021, that price must be paid for with record breaking inflation and eventual interest rate hikes that are depressing markets once again in 2022. So, while the major threat of COVID-19 may be diminished thanks to vaccinations, boosters, and diligent social distancing, the world economies are facing the consequences for inflating investments of all sorts – cryptocurrencies, NFTs, art, real estate, rent, and more.

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