Analysis of Economic and Pandemic Forces on U.S. Stock Market Index

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Abstract: Over the past century, research has been prevalent in the economic and financial literature on developing models to assist in the prediction of stock market price and stock market indices. Stock market price prediction is a complicated process, which has produced and conceptualized several theories regarding stock markets over the years. Most of these theories either try to explain the nature of stock markets or try to explain whether the markets can be manipulated through inefficiencies which often lead to financial gain for investors. Most of these past prediction models have utilized some form of quantitative-based regression analysis, including logit, stochastic, and multiple linear regression.

This research paper employs several multiple regression models that examine the effect of market and economic factors on three separate stock market indexes: the Dow Jones Industrial Average (DJIA), Standard and Poor's 500 (S&P 500), and NASDAQ. Using a group of data sets containing economic and market indicators, fourteen independent variables examined the influence of the chosen variables upon the daily closing prices of each of the three stock market indices. All three multiple regression models were identified as significant and several economic variables were found to be significant predictors in daily closing price of the respective stock market index. Future implications of these models upon the overall U.S. economy are explored.

Keywords: Stock market, financial markets, Dow Jones, Standard and Poor's, market prediction.

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Introduction

Financial markets have created a dramatic impact in many areas such as business, education, job creation, technology and ultimately on the overall U.S. economy (Hiransha, Gopalkrishnan, Menon, & Kp, 2018). Over several decades, investors and researchers alike have been interested in the development and testing of models simulating stock price behavior (Fama, 1995). However, analyzing stock market movements and price behaviors is extremely challenging because of the markets' dynamic nature, and number of variables available for testing (Abu-Mostafa & Atiya, 1996). According to Zhong and Enke (2017), stock markets are affected by many highly interrelated factors that include economic, political, psychological, and company-specific variables. Further complicating a detailed analysis of stock behavior, many investors do not follow the performance of individual stocks but instead study various stock market indices such as the Dow Jones Industrial Average (DJIA), Standard & Poor's 500 (S&P 500), and the National Association of Securities Dealers Automated Quotations (NASDAQ) exchange.

Unforeseen economic circumstances sometimes arise that shed a different light on financial markets. In March 2020, the World Health Organization (WHO) officially declared the COVID-19 outbreak a global pandemic, the first in more than a decade. In the U.S. alone, there have been more than 1.8 million total cases, which directly resulted in more than 106,000 deaths. In addition to the increasing number of diagnosed COVID-19 cases, this pandemic has led to a staggering economic crisis, affecting virtually every sector of the U.S. economy, and leaving more than 41 million employees unemployed. The economic health of the U.S. stock market has become a concern and an analysis will illuminate the relationship of various economic factors, including the COVID-19 pandemic, to market performance (Centers for Disease Control & Prevention, 2020).

This research paper examines the effect of relevant economic variables upon three stock market indices: the DJIA, S&P 500, and NASDAQ. Using a group of data sets, consisting of daily index closing prices of these three stock market indices and several economic variables, a series of multiple linear regression models examined the influence of fourteen independent variables upon these stock market index values. These analyses will provide insight into the performance of the stock market during these economic challenges.

Economic Theory of Market Prediction

Stock market price prediction is a complicated endeavor, which has resulted in several theories regarding stock markets being conceptualized over the years. These theories either try to explain the nature of stock markets or try to explain whether the markets can be manipulated and ultimately exploited for financial gain. The efficient-market hypothesis (EMH) in financial economics forms the assumption that asset prices are a function of all available information and at any point in time, the market price of a stock incorporates all available information about that stock. In other words, the stock is accurately valued until something changes. A direct implication is that it is impossible to "beat the market" consistently on a risk-adjusted basis since market prices should only react to new information. Because the EMH is framed in terms of risk adjustment, it only exhibits verifiable predictions when coupled with a particular model of risk. As a result, research in financial economics since the 1990s has largely focused on market anomalies, specifically deviations from specific models of risk (Fama, 1995).

The concept that market returns are difficult to predict originated with Bachelier (1900), who is credited with being the first person to model the stochastic process. This stochastic process, now commonly known as the Brownian motion, was an integral part of his PhD thesis *The Theory of Speculation*. Expanding the knowledge and literature in the financial economics arena were later studies by Cowles (1933), Mandelbrot (1963), and Samuelson (1965). In each of these studies, it was generally suggested that professional investors, in general, were unable to outperform the market. In a seminal study centered on event study methodology (Fama, Fisher, Jensen, & Roll, 1969), it was shown that stock prices, on average, react before a stock split, but have no movement afterwards.

Arguably the most relevant addition to the literature in the subject area of the efficient-market hypothesis was published by Fama (1970). In this research, tests of market efficiency were divided into three categories: weak-form, semi-strong form, and strong-form tests. These categories of tests refer to the information set utilized in the statement "prices reflect all available information." Weak-form tests utilize only the information contained in historical prices; semi-strong tests include information beyond historical prices, such as dividends, earnings announcements, and political/economic events; with strong-form tests being the most robust as they also contain private information. It is noteworthy that the strong-form category reflects all market, public, and private information which assures that no individual investor has monopolistic access to information (Naseer & Tariq, 2015).

According to EMH theory, price changes are unpredictable and forecasting a financial market is generally considered a hopeless endeavor. However, Abu-Mostafa & Atiya (1996) argued that the existence of so many price trends in financial markets and the undiscounted serial correlations among fundamental events and economic figures affecting the markets are only two of many pieces of evidence against the EMH. Certain researchers and investors disagree with EMH both empirically and theoretically, thereby shifting the focus of discussion from EMH to the behavioral and psychological aspects of market players (Naseer and Tariq, 2015). According to Zhong and Enke (2017), financial variables such as stock prices, stock market index values, and the prices of financial derivatives are therefore thought to be predictable. Certain widely accepted empirical studies show that financial markets are to some extent "predictable" (Chong & Ng, 2014). Criticism of EMH has given rise to an increasing number of studies that question the validity of EMH and introduce new and successful approaches that combine technical analysis indicators and chart patterns with methodologies from related disciplines such as artificial intelligence, data mining, econometrics, and statistics (Arevalo, Garcia, Guijarro & Peris, 2017).

Analytical Models

Generally speaking, the concepts of fundamental analysis and technical analysis are the two overarching approaches to analyze the financial markets (Park & Irwin, 2007; Nguyen, Kiyoaki, & Velcin, 2015). To invest in stocks and achieve high profits with low risks, investors have historically used these two major approaches to make decisions in financial markets (Arévalo et al. 2017). Fundamental analysis is mainly based on three essential aspects: (1) macroeconomic analysis such as Gross Domestic Product (GDP) and Consumer Price Index (CPI) which analyzes the effect of the macroeconomic environment on the future profit of a company; (2) industry analysis which estimates the value of the company based on industry status and performance; and (3) company analysis which analyzes the current operation and financial status of a company to evaluate its internal value (Hu, Liu, Zhang, Su, and Liu , 2015).

Different valuation techniques exist within fundamental analysis. For example, the average growth approximation technique compares an individual stock with other stocks in the same category to better understand valuations. Assuming two companies have the same growth rate, the one with the lower Price-to-Earnings (P/E) ratio is considered to be superior. Hence the fair price is the respective company's earnings times the "target" P/E. The P/E method is the most commonly used valuation method in the stock brokerage industry (Imam, Barker, & Clubb, 2008).

The constant growth approximation technique such as Gordon's growth model (Gordon & Shapiro 1956; Gordon, 1959) is one of the best-known classes of dividend discount models. It assumes that dividends of a company will increase at a constant growth rate forever but at less than the discount rate. Dutta, Bandopadhyay, and Sengupta (2012) demonstrated the value of fundamental analysis by utilizing various financial ratios to separate "good" stocks from stocks that perform poorly. These authors compared their single-year market return against a benchmark stock, which yielded an accuracy rating of 74.6%. This is one of the few scholarly studies that focused on using fundamental features (e.g. company-specific ratios) to identify stocks for investments.

Furthermore, Hu et al. (2015) grouped the domains of technical analysis into sentiment, flow-of-funds, raw data, trend, momentum, volume, cycle, and volatility. Sentiment represents the behaviors of various market participants. Flow-of-funds is a type of indicator used to investigate the financial status of various investors to pre-evaluate their strength in terms of buying and selling stocks, then, corresponding strategies can be adopted. Raw data include stock price series and price patterns such as K-line diagrams and bar charts. Trend and momentum are examples of price-based indicators; trend is used for tracing the stock price trends while momentum is used to evaluate the velocity of the price change and judge whether a trend reversal in stock price is about to occur. Volume is an indicator that reflects the enthusiasm of both buyers and sellers for investing, it is also a basis for predicting stock price movements. The cycle is based on the theory that stock prices vary periodically in the form of a long cycle of more than 10 years containing short cycles of a few days or weeks. Finally, volatility is often used to investigate the fluctuation range of stock prices and to evaluate risk and identify the level of support and resistance.

Sentiments can drive short-term market fluctuations which in turn cause disconnects between the price and true value of a company's shares. However, over long periods of time, a "weighing machine" kicks in as a company's fundamentals ultimately cause the value and market price of its shares to converge. A prominent example comes from the Nobel Laureate Robert Shiller, who demonstrated that stock prices are extremely volatile over the short term but somewhat predictable by their price-to-earnings ratios over long periods (Shiller, 2000). Diamond (2000) explained what returns to expect from the stock markets considering the economic scenario and suggested that in the future, returns could be substantially lower. Shiller (2000) also suggested that stocks are overvalued, and the bubble could burst anytime, which occurred during the "dotcom bubble burst."

Many new technologies and methods have been proposed over the years to try and predict stock prices via many avenues, thanks to the challenging and ever-changing landscape of stock markets (Chen & Chen 2016). Recent advancements in stock analysis and prediction fall under four categories: statistical, pattern recognition, machine learning (ML), and sentiment analysis. While these categories are generally grouped under the broader category of technical analysis, there are some machine learning techniques which also combine the broader categories of technical analysis with fundamental analysis approaches to predict the stock markets. With technology constantly evolving, these techniques have gained popularity and have shown promising results in the field of stock analysis in the recent past (Zhong & Enke, 2017).

COVID-19 Legislation

In response to the COVID-19 pandemic, Congressional leaders in the U.S. House and Senate set aside their political differences and passed a series of bipartisan bills aimed to assist in the economic recovery of the nation. To date, this series includes three distinct bills of legislation, each addressing specific areas of the economy with various levels of funding.

Coronavirus Preparedness & Response Supplemental Appropriations Act

The initial round of Federal funding in response to the pandemic, Coronavirus Preparedness & Response Supplemental Appropriations Act, was signed into law by President Trump on March 6, 2020. This bill provided $8.3 billion in emergency funding appropriated to various Federal agencies to respond to the coronavirus outbreak. Of the $8.8 billion, $6.7 billion (81%) was designated to domestic agencies and $1.6 billion (19%) for international response.

Of the $6.7 billion earmarked for domestic agencies, the vast majority ($6.2 billion) flowed to the Department of Health and Human Services (HHS). Highlights included vaccine research and funding for the Centers for Disease Control and Prevention (CDC), medical devices for the Food and Drug Administration (FDA), and funding for disaster loan programs for the Small Business Administration (SBA). Internationally, various programs were funded for economic support and other needs within the U.S. State department for U.S. embassies. Overall, this act created conjecture as many felt the level of funding was paltry when compared to the expenses generated in fighting the pandemic (H.R. 6074, 2020).

Family First Coronavirus Response Act

On March 18, 2020, Congress passed the Families First Coronavirus Response Act, which is slated to expire at the end of December 2020. The Act's multiple divisions specify the added assistance provided in the general areas of nutrition, family and medical leave, unemployment, sick leave, and tax credits. Division C of the Families First Act, known as the

Emergency Family and Medical Leave Expansion Act, amends the original Family and Medical Leave Act of 1993 to include a qualifying need related to caring for a child due to the public health emergency COVID-19. Employers must provide compensated leave to employees unable to appear at the physical workplace or perform tasks virtually due to the coronavirus public health emergency. Division E, the Emergency Paid Sick Leave Act, requires employers to pay sick leave to employees unable to work or telecommute due to the impact of COVID-19. Examples of qualifying reasons include government quarantine orders, coronavirus illness or symptoms, and providing care for family members due to COVID-19 precautions.

Finally, the Act provides relief for employers through a tax credit. Division G, Tax Credits for Paid Sick and Paid Family and Medical Leave, offers a limited payroll tax holiday for certain employers who must pay employees under divisions D and E of this legislation. The credit for employers is the 6.2 percent social security portion of FICA. The credit is 100 percent of qualifying wages, which also applies to self-employed individuals. A maximum of $10,000 in wages per employee is eligible for the paid leave credit. The sick leave maximum ranges from $2,000 to $5,110 in total depending on the justification the employee is unable to work (H.R. 6201, 2020).

Coronavirus Aid, Relief and Economic Security (CARES) Act

Congress passed the CARES Act approximately one week after the Families First Act on March 27, 2020. Carrying appropriations and funding of $2 trillion, CARES provides programs across seven general sectors of the U.S. economy. Components of the act and funding to each sector are illustrated in Table 1 (H.R. 748, 2020).

Table 1: CARES Act Components

Component	Amount of Funding	% of Total Funding
Individuals	$560 Billion	28.00
Corporations	$500 Billion	25.00
Small Business	$377 Billion	18.85
State & Local Government	$339.8 Billion	16.98
Public Health	$153.5 Billion	7.68
Education	$43.7 Billion	2.19
Safety Net	$26 Billion	1.30
Total	**$2.00 Trillion**	**100.00%**

The CARES Act provides for advance refunding of the payroll tax credits enacted in the Families First Act. In addition, penalties are waived for not depositing any payroll taxes expected to be refunded. Employers can use IRS form 7200 for Advance Payment of Employer Credits due to COVID-19 to request the advance payment. Other payroll tax changes specified in section 2302 of the Act include the delay of payments of employer payroll taxes. The payroll tax deferral period extends payments of 2020 employer payroll taxes. One-half of the taxes are due by December, 2021 and the remaining one-half are due by December, 2022.

Section 2301 of the CARES Act outlines another business provision affecting payroll taxes. The employee retention credit aims to help businesses keep employees on the payroll. The credit is for employers who had to close or limit operations due to the coronavirus disease and governmental suspension of nonessential trade and business. This credit offers a limited payroll tax holiday for certain employers on 50% of qualifying wages with a maximum of $10,000 per employee. Any wages used to claim the Families First payroll tax credits for sick leave and paid family leave would not be eligible for the employee retention credit. In addition, if the employer takes part in the SBA paycheck protection program the credit would not apply (Nevius & Schreiber, 2020).

Methodology & Data Collection

Historical data was collected from various sources that were used to represent the predictor and response variables necessary to build the multiple linear regression models for this study. Because the initial diagnosis of COVID-19 in the U.S. occurred on January 21, 2020, this date was used as the separation point between two time periods utilized for this study. The time period prior to the initial COVID-19 diagnosis consisted of 113 days of stock market operations from August 8, 2019, until January 20, 2020. Additionally, data chosen to represent the time period following the initial COVID-19 diagnosis consisted of an identical time period of 113 days of stock market operations from January 21, 2020, until June 30, 2020. At the time of data collection for this study, these time periods were the most current stock market index and economic data available.

To represent the dependent variables, daily closing data (in U.S. dollars) was collected online from Yahoo! Finance for three stock market indexes: the Dow Jones Industrial Average (DJIA), Standard & Poor's 500 (S&P 500), and the NASDAQ composite. The Dow Jones is one of the most quoted financial barometers and has become synonymous with financial markets in general. Created in 1896 with twelve stocks, the Dow was expanded to include 30 stocks in 1929 and serves as a stock market proxy in addition to an overall indicator of market health. However, detractors dispute the validity of the index and consider the Dow to be an inadequate representation of the stock market when compared to a broader market index such as the S&P 500. Only having 30 large cap stocks, not being weighted by market capitalization, and not using a weighted arithmetic mean are often listed among DJIA's shortfalls (Ganti, 2020). Additionally, the NASDAQ composite index tracks 3,000 stocks, many of which are younger companies in the technology, biotechnology, and pharmaceutical sectors. Using this triad of indexes added a more robust approach to the study and makes the results more relevant.

To complete the regression models, fourteen unique independent variables were utilized. Each of these predictor variables were chosen to represent various economic indicators, including employment, unemployment rates, consumer and producer indexes, retail, and housing data. Additionally, data representing COVID-19 cases and deaths were added to the model, along with dichotomous variables created to capture effects of time periods and Federal stimulus programs. A listing of the independent variables employed in each of the three regression models are listed in Table 2.

Table 2: Predictor Variables for Regression Models

COVID-19 Cases	Producer Price Index (PPI)
COVID-19 Deaths	Purchasing Managers Index (PMI)
Unemployment Rate (%)	National Retail Sales
Unemployment Claims	New Housing Starts
Non-Farm Payroll	Gross Domestic Product (GDP)
Consumer Confidence Index (CCI)	COVID-19 Dummy
Consumer Price Index (CPI)	Stimulus Dummy

Results of Study

A series of quantitative analyses utilizing multiple linear regression were conducted to examine the strength of any possible relationships between the economic predictor variables and respective stock market indices. Specifically, the following relationships were examined:

1. The strength of the fourteen economic variables in predicting daily closing price of the Dow Jones Industrial Average stock index.
2. The strength of the fourteen economic variables in predicting daily closing price of the Standard & Poor's 500 stock index.

3. The strength of the fourteen economic variables in predicting daily closing price of the NASDAQ stock index.

A multiple linear regression was calculated to predict the daily closing price of the Dow Jones Industrial Average stock index based on 14 independent variables. A significant regression equation was found [$F(14, 211) = 100.76$, $p < .01$], with an R-square of .869. This coefficient of determination indicated that 86.9% of the variance in daily closing price can be explained by the regression model. The One-way Analysis of Variance (ANOVA) output is presented in Table 3.

Table 3: Analysis of Variance (ANOVA) Table

Source	DF	Sum of Squares	Mean-square	F-ratio	*p*-value
Regression	14	999,270,184	7,137,6442	100.76	$p < .01$*
Error	211	149,473,441	708,405		
Total	225	114,874,3624			

* significant at the .05 level

This analysis tested for multicollinearity, which can occur when two or more predictors in the model are correlated and provide redundant information about the response variable. Multicollinearity was measured by variance inflation factor (VIF) and examined for tolerance levels. VIF measurements for each of the 14 explanatory variables included in the multiple regression model were found to be less than 10 (VIF<10). These tolerance levels were found to within an acceptable range, indicating that multicollinearity is not present in the model (Curto & Pinto, 2011). All relevant multiple linear regression results and variables are illustrated in Table 4. While the overall multiple regression model was found to be significant, some of the fourteen predictor variables did not make a significant contribution to the regression model. Exactly one-half (seven) of the independent variables utilized in the study were found to be significant predictors of the daily closing price of the Dow Jones Industrial Average index.

Table 4: Multiple Linear Regression Results (DJIA)

	Coefficient	*t*-statistic	*p*-value
Constant	-281329	-3.98	$p < .01$*
COVID-19 Cases	-0.0180	-1.09	.278
COVID-19 Deaths	0.2330	1.41	.159
Unemployment Rate	-80.0	-0.15	.880
Unemployment Claims	0.000062	1.96	.051
Non-Farm Payroll	0.000304	1.10	.272
Consumer Confidence Index (CCI)	88.20	2.62	$p < .01$*
Consumer Price Index (CPI)	1195.0	4.25	$p < .01$*
Producer Price Index (PPI)	581.0	1.29	.198
Purchasing Managers Index (PMI)	-5.0	-0.05	.959
National Retail Sales	0.000000	2.97	$p < .01$*
New Housing Starts	-0.1481	-4.50	$p < .01$*
Gross Domestic Product (GDP)	-0.000000	-4.07	$p < .01$*
COVID-19 Dummy	-1249.0	-3.73	$p < .01$*
Stimulus Dummy	-6002.0	-14.47	$p < .01$*

* significant at the .05 level

A second multiple linear regression was calculated to predict the daily closing price of the S&P 500 index based on the same 14 independent variables. A significant regression equation was found [$F(14, 211) = 82.15$, $p < .01$], resulting in an R-square of .845. This coefficient of determination indicated that 84.5% of the variance in daily closing price can be explained by the regression model. The Analysis of Variance (ANOVA) output is presented in Table 5.

Table 5: Analysis of Variance (ANOVA) Table

Source	DF	Sum of Squares	Mean-square	F-ratio	*p*-value
Regression	14	9,164,080	654,577	82.15	$p < .01$*
Error	211	1,681,320	7,968		
Total	225	10,845,400			

* significant at the .05 level

This second multiple also analysis tested for multicollinearity, observing VIF measurements for each of the 14 explanatory variables were found to be less than 10 (an acceptable tolerance). All relevant multiple linear regression results and variables are illustrated in Table 6. While the overall model was found to be significant, not all of the fourteen predictor variables made a significant contribution to the regression model. However, more than one-half of the independent variables were found to be significant predictors of daily closing price of the S&P 500 index.

Table 6: Multiple Linear Regression Results (S&P 500)

	Coefficient	***t*-statistic**	***p*-value**
Constant	-42831	-5.71	$p < .01$*
COVID-19 Cases	-0.00228	-1.30	.196
COVID-19 Deaths	0.269	1.59	.112
Unemployment Rate	63.3	1.14	.258
Unemployment Claims	0.000010	3.01	$p < .01$*
Non-Farm Payroll	0.000077	2.64	$p < .01$*
Consumer Confidence Index (CCI)	8.56	2.40	.017*
Consumer Price Index (CPI)	157.9	5.30	$p < .01$*
Producer Price Index (PPI)	63.8	1.34	.182
Purchasing Managers Index (PMI)	-14.2	-1.33	.184
National Retail Sales	0.000000	3.90	$p < .01$*
New Housing Starts	-0.01600	-4.58	$p < .01$*
Gross Domestic Product (GDP)	-0.000000	-4.61	$p < .01$*
COVID-19 Dummy	-115.5	-3.25	$p < .01$*
Stimulus Dummy	-645.3	-14.67	$p < .01$*

* significant at the .05 level

Finally, a third multiple linear regression was calculated to predict the daily closing price of the NASDAQ stock index based on the aforementioned 14 predictor variables. A significant regression equation was found [F(14, 211) = 119.64, $p < .01$], resulting in an R-square of .816.

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This coefficient of determination indicated that 81.6% of the variance in daily closing price can be explained by the regression model. The Analysis of Variance (ANOVA) output is presented in Table 7.

Table 7: Analysis of Variance (ANOVA) Table

Source	**DF**	**Sum of Squares**	**Mean-square**	**F-ratio**	***p*-value**
Regression	14	104,695,387	7,478,242	119.64	$p < .01$*
Error	211	13,189,162	62,508		
Total	225	117,884,549			

* significant at the .05 level

As in the aforementioned two models, VIF measurements denoting the presence multicollinearity were observed to be acceptable (VIF<10). In addition to the ANOVA output, all relevant multiple linear regression results and variables are illustrated in Table 8. While the overall model was found to be significant, not all of the fourteen predictor variables made a significant contribution to the regression model. More than one-half of the independent variables were found to be significant predictors of daily closing price of the NASDAQ stock market index.

Discussion

In most of the past academic research, it was suggested that analyzing stock price behavior and movement is a challenge due to the complex interrelated factors and variables available for testing. Economists and investors often analyze various financial variables for their influence on the stock market and on the U.S. economy. The recent COVID-19 pandemic affected the U.S. economy and economies worldwide. Government officials reacted to this unexpected health crisis by implementing various measures to mitigate the spread of the coronavirus. Businesses and organizations considered nonessential were closed and many employees were barred from working. The resulting financial crisis affected practically all areas of the U.S. economy. In response, the U.S. government supplied financial relief to workers and businesses through economic stimulus plans. This analysis explores the relationship of common economic indicators to market performance considering the COVID-19 pandemic.

Table 8: Multiple Linear Regression Results (NASDAQ)

	Coefficient	***t*-statistic**	***p*-value**
Constant	-156606	-7.46	$p < .01$*
COVID-19 Cases	-0.00199	-0.40	.686
COVID-19 Deaths	0.0524	1.07	.285
Unemployment Rate	399.0	2.55	.719
Unemployment Claims	7.17	5.93	.011*
Non-Farm Payroll	0.000384	4.69	$p < .01$*
Consumer Confidence Index (CCI)	19.8	1.98	.049*
Consumer Price Index (CPI)	525.7	6.29	$p < .01$*
Producer Price Index (PPI)	177.0	6.29	.187
Purchasing Managers Index (PMI)	-70.8	-2.37	.019*
National Retail Sales	0.000000	5.00	$p < .01$*
New Housing Starts	-0.04577	4.68	$p < .01$*
Gross Domestic Product (GDP)	-0.000000	-5.74	$p < .01$*
COVID-19 Dummy	-192.3	-1.93	.055
Stimulus Dummy	-1747.0	-14.18	$p < .01$*

* significant at the .05 level

The results obtained in this analysis show all three of the multiple linear regression models were significant. At least one-half of the predictor variables chosen for this study were found to be significant predictors of the daily closing price of all three of respective stock market indexes. Furthermore, the tested regression models yielded correlation coefficients (R-square) of greater than 80%, which indicates very strong predictions models leading to more than 80% of the variability in closing stock index price attributed to the independent variables chosen for the study.

A closer examination reveals that gross domestic product, new housing starts, and national retail sales were significant predictors of the daily closing price of the Dow Jones, S&P 500, and NASDAQ. These results are similar to a study by MSCI Barra (2010), which examined the link between GDP growth and equity returns. A comparison of earnings-per-share, price returns, and GDP growth for selected countries showed average stock prices have followed GDP. In addition, simple supply-side models used to forecast stock prices show a positive but imperfect link between GDP and stock returns. However, this complex issue involves assumptions and theories that must be considered in any detailed analysis. New housing starts and national retail sales are both leading macroeconomic indicators with consumer spending making up two thirds of GDP. Strength in these indicators generally corresponds with positive movement in the stock market. Data compiled by Haver Analytics over a fifteen-year period shows stock market performance and national retail sales have been highly correlated. Increases in retail sales may encourage future gains in the stock market (Beals, 2016).

In addition, the consumer confidence index (CCI) and the consumer price index (CPI) were significant predictors of the daily closing price of all three indexes. A one-point increase in the CCI would indicate an increase in the Dow Jones, S&P 500, and NASDAQ of $88.2, $8.56, and $19.8, respectively. This differs from prior research showing the consumer confidence index captures broad economic trends and has use for forecasting non-stock market wealth growth and labor earnings (Ludvigson, 2004). A one-unit increase in the CPI causes an increase in the DJIA, S&P 500, and NASDAQ of $1,195, $157.9, and $525.7, respectively. However, Frankel and Saiki (2017) note the CPI has a highly significant positive correlation with the bond market but the effect on the stock market is open to interpretation.

Of the three labor-related variables evaluated in the study the unemployment claims and non-farm payroll were significant predictors of the daily closing price for both the S&P 500 and NASDAQ. While the stimulus dummy variable was significant for all three stock market indices, a negative correlation indicated that the time period after the stimulus plan caused a decrease in the closing prices of all three stock indexes. The COVID-19 dummy variable was significant for the DJIA and the S&P 500, causing an overall decline in index points after the initial diagnosis of COVID-19 in the U.S. The health-related variables, COVID-19 cases and deaths were not significant predictors of the daily closing price of any of the three stock market indices. This differs from expectations that the number of COVID-19 cases and deaths would have a significant negative impact on the stock market closing prices.

Conclusion

The effects of the COVID-19 pandemic and the economic stimulus plans on the stock market will continue to unfold as governments enact and remove various restrictions on workers, the public, and businesses. A similar data collection in the future could supply more data and yield further insights into the possible development of analytical models. Future research could analyze the apparent lack of connection between the distressed economy and the better than expected stock market performance. Factors that could be explored in this area are the impact of the Federal Reserve Board's monetary policy during the pandemic and their support of small businesses and nonprofit organizations through the Main Street Lending program and the Paycheck Protection Program.

Once the current stimulus programs expire and extended unemployment benefits end, the expected decline in consumer spending and confidence could affect the markets. The proposed future stimulus packages may or may not reach the level of earlier stimulus plans resulting in possible short-term pains which could be evaluated against potential long-term gains. In the area of health there is optimism due to COVID-19 death rates being lower than initially expected, promising medical treatments for those with coronavirus, and major funding to find a coronavirus vaccine. This optimism may change if the COVID-19 deaths rise which could then have a significant negative impact on the equity markets (Wilmington Trust, 2020). Investigating the impact on the economy and stock market will be a topic of interest for years to come.

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