Assessing the Impact of COVID-19 on Automobile Sales in the United States

Lumin Chen*

Leicester International Institute, Dalian University of Technology, Liaoning, 350000, China

*Corresponding author: lc489@student.le.ac.uk

Abstract. This comprehensive study delves into the COVID-19 pandemic's substantial impact on the American automotive industry, emphasizing its specific effects on sales volume, production, and market demand. It thoroughly examines the sector, including an in-depth analysis of the supply chain and market dynamics. Utilizing a time series model, the research meticulously analyzes data from the onset of the pandemic in early 2020, offering a quantitative assessment of its impact. The findings reveal a significant influence of COVID-19, particularly in the decline of sales volume, which has been alarming for industry stakeholders. Production processes have also faced severe disruptions, leading to challenges in meeting market demand efficiently. Moreover, there has been a notable shift in market demand, reflecting changing consumer preferences and the economic uncertainties triggered by the pandemic. These changes have posed considerable challenges, necessitating strategic adaptations in marketing, production, and overall business strategies within the automotive sector. The study underscores the need for resilience and innovative approaches to effectively address these issues. The study concludes that COVID-19 has had a profound and multifaceted impact on the American automotive industry. It not only highlights the current challenges but also proposes strategic measures for overcoming these hurdles. The study offers valuable insights for future development and innovation in the sector.

Keywords: COVID-19; Automotive industry; ARIMA model; dynamic regression.

1. Introduction

The COVID-19 pandemic, which swept across the globe in early 2020, brought about unprecedented challenges and disruptions in various industries [1]. the pandemic caused a cascade of events that reverberated through the entire automotive supply chain and market dynamics [2, 3]. In the public eye, the impact of the pandemic on the U.S. automotive industry has primarily been attributed to two events: the widespread automotive production halts in 2020 [4], and the semiconductor chip shortage in 2021 [5]. However, the factors influencing the automotive market are often diverse. Conducting research on these factors can provide a more comprehensive understanding of the pandemic's impact on the U.S. automotive market from various perspectives. This research holds immense significance for shaping future policy initiatives.

In discussing these impacts, this paper will draw from a variety of reputable sources. Research studies and reports from organizations such as the International Monetary Fund (IMF), the International Trade Administration (ITA), the Center for Automotive Research (CAR), and the United States Bureau of Economic Analysis (BEA) will be utilized to provide data and insights into the consequences of the pandemic on the American automotive industry. Additionally, analyses and articles from authoritative sources like The New York Times, The Wall Street Journal, and automotive industry publications like Automotive News will be referenced to provide in-depth context and perspective.

The pandemic's first major blow to the industry was the abrupt shutdown of production facilities due to government-mandated lockdowns and health concerns [6]. As manufacturing plants ground to a halt, supply chains experienced severe disruptions, leading to a shortage of essential components, most notably semiconductors. These shortages not only delayed production but also exposed the industry's overreliance on a few key suppliers [7]. Consumer behavior also changed significantly during the pandemic [8]. The economic uncertainty and health concerns prompted consumers to rethink their transportation needs. A shift towards remote work reduced the demand for traditional commuter vehicles, and the financial strain on households caused a slump in new car purchases.

At the same time, interest in electric and sustainable vehicles grew [9], accelerating an ongoing transition in the industry [10]. In response to the crisis, automakers had to adapt quickly. They accelerated digital transformation efforts, adopting online sales models and incorporating advanced safety features to meet new consumer demands. Moreover, the pandemic's impact on the workforce, with remote work becoming the norm for many, reshaped labor dynamics within the automotive industry. In the course of this paper, the measures implemented by the American government to bolster the industry during the pandemic will be examined, ranging from financial aid to policy modifications. Additionally, the resilience, adaptability, and innovation demonstrated by the industry, which enabled it to withstand the crisis and emerge in a transformed state, will be discussed.

In summary, the COVID-19 pandemic left no facet of the American automotive industry untouched. From manufacturing disruptions and supply chain challenges to shifting consumer preferences. Constructing an appropriate time-series model through exploration of diverse data sources and expert analyses this paper aims to provide a comprehensive understanding of how the pandemic impacted the American automotive sector and how it shaped the industry's future.

2. Methods

2.1. Data Source

The data for this article primarily originates from the Federal Reserve Economic Database (FRED). Table 1 displays the main variables and identifies the types of variables in the dynamic regression model.

Table 1. Variable Description

Variable Number	Explanation	Variable Type
TOTALSA	Car Sales Volume	Dependent Variable
PCE	Personal Income	Independent Variable
DSPIC96	Disposable Income	Independent Variable
DAUPSA	Car Production Volume	Independent Variable
UNRATE	Unemployment Rate	Independent Variable
TRFVOLUSM227NFWA	Mileage Traveled	Independent Variable

The aforementioned variables are chiefly utilized to quantify consumer behavior and principal economic activities, as well as serve as multidimensional economic indicators that impact car sales volume.

2.2. Method Introduction

The main objective of this study is to investigate the impact of the COVID-19 pandemic on overall car sales. In our research, we divide the overall sample into two parts based on the outbreak of the pandemic: Pre-COVID outbreak (COVID = 0) and during the COVID outbreak (COVID = 1). We focus on two subdivisions of research directions: assessing the impact of the pandemic on car sales and evaluating the predictive performance of the dynamic regression model.

2.2.1 Model construction

ARIMA Model: An ARIMA model is constructed using Pre-pandemic car sales data, and the AIC (Akaike Information Criterion) is utilized to select the parameters for the ARIMA model.

Dynamic Regression Model: A dynamic regression model is also built using pre-pandemic car sales data. This model allows the inclusion of external relevant variables while also integrating the residual terms from the ARIMA model, taking into account the effects of external variables and the time lag of the internal dependent variable. In this study, the dynamic regression model incorporates Personal Income, Disposable Income, Car Production Volume, Unemployment Rate, and Mileage Traveled as independent variables.

2.2.2 Model prediction

Utilizing the trained ARIMA and dynamic regression models, predictions are made for car sales volumes during the pandemic period. Additionally, the difference between the model's forecasted values and the actual figures is calculated.

2.2.3 Statistical testing

The final prediction results are evaluated using a T-test to assess whether the pandemic has caused a structural change in car sales data.

2.2.4 Model assessment

In order to compare the predictive performance of the dynamic regression model and the ARIMA model, data from before the pandemic is extracted for training and evaluation purposes. Both models are trained using this pre-pandemic data. For the period during the pandemic, predictions are made, and the performance of the two models is compared using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to determine how each model performs on both the training and testing datasets.

3. Results and Discussion

3.1. Stationary Test

Before fitting a time series model, it is essential to perform a stationarity test on the time series to avoid the phenomenon of spurious regression. In this study, the unit root test (ADF test) is used to determine the stationarity of sales volume during the sample period. The ADF test p-value for the original sales volume series is 0.03459, which is significantly less than 0.05. Therefore, the null hypothesis of "having a unit root" is rejected at the 5% significance level, confirming that the original sales volume series is a stationary time series (table 2).

Table 2. ADF Test P-value

Order	Sales volume
Primitive sequence	0.03459

3.2. ACF Plot and PACF Plot

The ACF chart illustrates the magnitude of autocorrelation at various lag values. In this particular chart, we observe a high ACF at lag 1, which then gradually declines. As the lag values increase, the absolute value of the autocorrelation coefficient progressively diminishes, yet remains significantly non-zero across most lag values. The PACF chart displays the correlation of lag values after the influence of intervening values has been removed. For this chart, it is evident that PACF is significant only at lag 1, after which it quickly drops close to zero and becomes insignificant (remaining within the confidence interval) for subsequent lags. The ACF plot of the original sales volume series exhibits significant tailing, while the PACF plot shows a clear cut-off characteristic at lag one (Fig 1, 2).

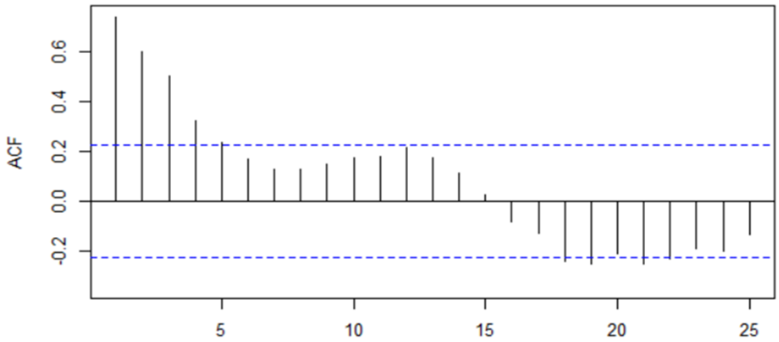

Fig. 1 Sales Volume Series ACF

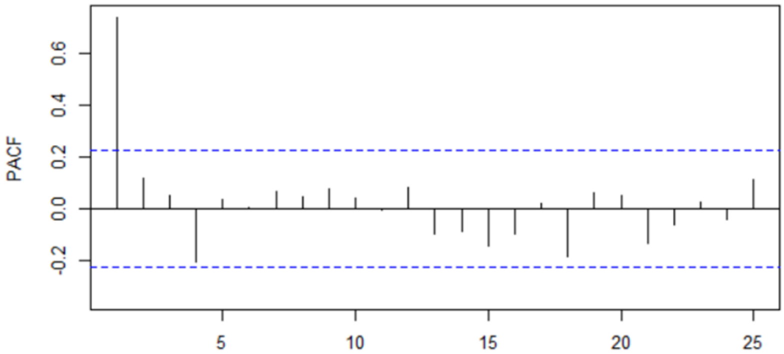

Fig. 2 Sales Volume Series PACF

3.3. Model Fitting

The ARIMA model is used to fit the data prior to the pandemic, and the criterion of the smallest AIC is adopted to select the optimal parameters. The ARIMA(0,1,1) model is finally determined as the best model. For the dynamic regression model, the overall model is divided into an ARIMA error term component and a regression component. The overall model is as follows (table 3, 4):

Table 3. AIC values for sales volume fitted with different ARIMA models.

ARIMA Model	AIC value
ARIMA(0,1,1)	74.81
ARIMA(1,0,0)	86.49
ARIMA(0,0,1)	107.69
ARIMA(2,0,0)	86.03
ARIMA(0,0,2)	103
ARIMA(1,0,2)	87.74
ARIMA(2,0,1)	87.9

Table 4. Model fitting effect.

	ARIMA	Dynamic regression model
ARIMA	(0,1,1)	(2,0,2)
Sigma2	0.1521	0.1114
Log Likelihood	-35.35	-19.79
AIC	74.71	61.57
AICc	74.87	61.57
BIC	79.34	65.7
ar1	-0.3026	1.6894
ar2		-0.9178
ma1		-1.475
ma2		0.6378

$$\mathrm{TOTALSA_t} = 25.8699 - 4 * 10^{-4} * \mathrm{PCE_t} + 0 * \mathrm{DSPIC96_t} + 0.0088 * \mathrm{DAUPSA_t} - 1.2202 * \mathrm{UNRATE_t} + 0 * \mathrm{TRFVOLUSM227NFWA_t} + \varepsilon_t \quad (1)$$

Where ε_t is the error term of ARIMA(2,0,2).

3.4. Assessing the Impact of the Pandemic on Automobile Sales Volum

To compare the fit of the two models, the AIC and BIC values of the ARIMA model and the dynamic regression model are compared. The dynamic regression model has lower AIC and BIC values than the ARIMA model, indicating a better fit for the dynamic regression model.

As for the interpretation of the coefficients in the dynamic regression model: The coefficient for personal consumption expenditures (PCE) is close to 0, suggesting that personal consumption expenditures do not have a significant impact on automobile sales when controlling for other variables. The coefficient for real disposable personal income (DSPIC96) is 0.0088, indicating a positive correlation between automobile production and sales. The coefficient for the unemployment rate (UNRATE) is -1.2202, indicating that an increase in the unemployment rate suppresses the growth of automobile sales. The coefficient for vehicle miles traveled (TRFVOLUSM227NFWA) is 0, suggesting that pre-pandemic driving mileage is not a relevant variable for automobile sales. Through comparative analysis, the dynamic regression model has a higher degree of fit than the ARIMA model and also possesses greater explanatory power with the introduction of other variables.

3.5. Model Prediction and Testing

According to the T-test results, the predicted values of the ARIMA model are significantly overestimated when compared with the actual figures, with a P-value of 0, which is far below the significance level of 0.01 (Fig 3). This indicates that there is a significant difference between the predicted values of the ARIMA model and the actual values, with the predictions being significantly higher. From a practical standpoint, the ARIMA model was built using only pre-pandemic car sales data for training, and the structural changes in car sales due to the significant external factor of the pandemic were not captured. The ARIMA model, which focuses solely on past data of car sales, is unable to reflect these trend changes promptly, also highlighting the fundamental impact of the pandemic on car sales volumes. On the other hand, the predicted data from the dynamic regression model are closer to the actual values, with a P-value of 0.0265, which is above the significance level of 0.01. This suggests that there is no significant difference between the predicted values of the dynamic regression model and the actual values. From the graphs, we can analyze that the dynamic regression model accurately captured a significant decline in car sales early in the pandemic, and this response was much stronger than the actual change in values. This indicates that the impact of the pandemic as an external factor had a significant suppressive effect on car sales, and also shows that the dynamic regression model, by introducing external variables and lag factors, effectively predicted the potential impact of the pandemic on car sales, thereby significantly enhancing the model's predictive accuracy and reliability (table 5).

Table 5. Test Results

Model	Estimate	Statistic	Parameter	P_Value	CI_Low	CI_High
ARIMA	-2.5109	-8.7981	43.0000	0.0000	-3.0865	-1.9354
Dynamic Regression	1.0016	2.2973	43.0000	0.0265	0.1223	1.8810

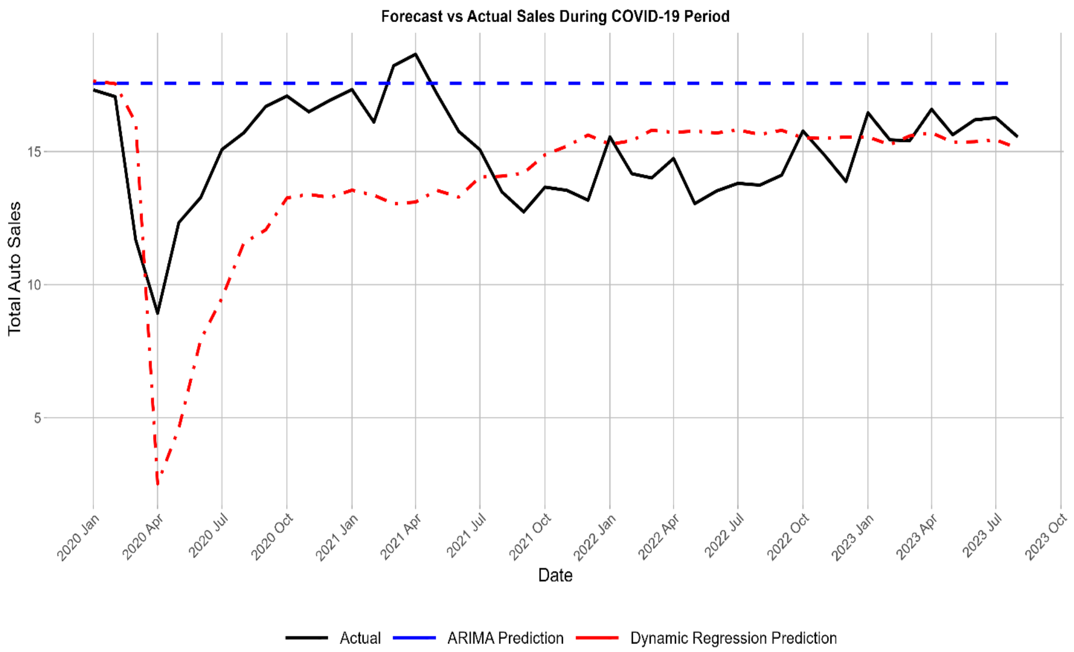

Fig. 3 Forecast vs Actual Sales During COVID-19 Period

3.6. Comparison of Predictive Performance

On both the training and testing sets, across all forecast error metrics—ME (Mean Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MPE (Mean Percentage Error), MAPE (Mean Absolute Percentage Error), MASE (Mean Absolute Scaled Error)—the dynamic regression model outperforms the ARIMA model. This indicates that the dynamic regression model is not only effective in anticipating the suppressive effect of the pandemic on car sales but also far surpasses the ARIMA model in terms of predictive accuracy.

3.7. Discussion

The impact of the pandemic on car sales can be inferred from the predictive results of the ARIMA model and the dynamic regression model. Firstly, the ARIMA model, which relies solely on the single variable of car sales to build the prediction model, represents a single variable's intrinsic trend; in other words, predictions made using the ARIMA model will continue the original data trend into the future. It has been observed that during the pandemic, predictions made with the ARIMA model significantly overestimated sales, suggesting that in the absence of the pandemic, car sales would have been higher than what was actually seen. This indicates that the pandemic has notably suppressed car sales, leading to a structural change in sales volumes.

The dynamic regression model, on the other hand, introduces potential feedback variables to assist in prediction, making the results very close to the actual numbers. In some extreme cases, these auxiliary variables can act as leading indicators to reflect external shocks. At the onset of the pandemic, it was clearly observed that car sales predicted by the dynamic regression model experienced a cliff-like drop, indicating that the leading auxiliary variables played a role in reflecting the impact of the pandemic. This dramatic downturn also suggests that the pandemic had a significant suppressive effect on car sales. The overall trend indicates that the impact of the pandemic on car sales was initially severe and then gradually began to recover.

4. Conclusion

The analysis above shows that the pandemic has had a significant impact on the sales volume of automobiles in the United States, and this impact is multifaceted. Therefore, it is necessary to formulate relevant strategies for these influencing factors. In conjunction with the independent variables used in the dynamic regression model, some suggestions can be made.

Firstly, the government can implement policies to stimulate job growth, especially in the automotive industry. This may include providing tax incentives to companies that retain or increase their workforce, as well as subsidies for employee training programs to re-skill workers to meet the industry's evolving demands. Secondly, stimulating automobile demand can be achieved by increasing the disposable income of citizens. This could be done through temporary tax reductions, direct stimulus payments, or expanding unemployment benefits. Ensuring that consumers have sufficient disposable income is critical to reigniting consumer spending on major goods like automobiles. Lastly, the government can support automobile production by offering low-interest loans and subsidies to manufacturers to reduce production costs and encourage innovation, thereby enhancing output and efficiency. Through these comprehensive measures, favorable conditions can be created for the revival of the automobile industry.

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