Impact of the COVID-19 Pandemic on Retail Sales of Health and Personal Care Stores in the United States

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Abstract. In recent years, as a result of the Covid-19 pandemic, the health and personal care stores have been remarkably affected in a wide range of aspects. This became one of the reasons why medical staff felt pressure, leading to quite a number of staffs resigning, and meanwhile the management pattern of medical employees changes and seems to be more strict. Furthermore, the prevalence of Covid-19 pandemic also causes some mental diseases such as sleeping disturbance, anxiety as well as skin problems whether for adults or younger people. As a consequence, the health and personal care industry has been brought to light. This industry has become high in demand like never before. Therefore, complemented by daily and monthly U.S. coronavirus cases, retail sales of health and personal care stores in the USA is a time series worth analyzing. Best-fit ARIMA model for the retail sales is determined to be ARIMA (2, 2, 3) to forecast future health and personal care retail sales in hope of supporting the industry prepare for the ongoing pandemic and in case of another crisis. Regression models are built to find correlations between health and personal care retail sales and coronavirus cases. Additionally, this paper extended ARIMA by employing dynamic regression model which generates a more accurate forecast from regression with ARIMA (0, 1, 1) errors.

Keywords: Retail sales of health and personal care stores; COVID-19 pandemic; ARIMA model.

1. Introduction

The ongoing pandemic has brought public health to light. Both professionals and laypeople are trying their best to minimize the spread of the COVID-19 pandemic, which had a significant impact on the retail sales of health and personal care stores. By analyzing this time series trend, the healthcare industry could prepare themselves and consumers better in case of another crisis. The time series chosen about Retail Sales of Health and Personal Care Stores in the USA is from FRED Economic Data [1]. Its original data is collected by the U.S. Census Bureau. From the range of time over decades, it is easy to get a comprehensive view of how sales normally were before a pandemic, how the urgency of a pandemic affects the sales, and how sales adapted to the pandemic.

All the data is processed by R on the IDE R-Studio. The chosen time series is divided into three sections: pre-COVID, post-COVID, and the two series combined. To process the data, besides going through the stationarity (unit root) and white-noise (Ljung-Box) test, the non-stationary data are stationarized by applying logarithms and differencing, so that the data went from exponential trends to linear. Autocorrelation function (ACF) graph and partial autocorrelation (PACF) graph are used to find the initial number of ARIMA models by looking at the number of lags above the critical value, determining whether they are tail-off or cut-off, then auto.arima ( ) is used to confirm the best-fit ARIMA model. The ARIMA model forecasts for pre-COVID data is compared with the observed data. The model for the entire data set is used to forecast future retail sales up to the 2030s. Then residuals are checked for each ARIMA model. Regression models are built based on the stationarized data with coronavirus cases from CDC on the x-axis, and retail sales on the y-axis to find possible correlations [2].

2. Facts about the COVID-19 and Health Care

The prevalence of Covid-19 pandemic now has become a global issue, and the health care as well as personal care industries have been significantly influenced because of this, which is shown in various aspects.

2.1 Staff Experience and Management in Health Care Stores

There's no doubt that health care workers play an essential role in reducing the possibility of COVID-19 infection. However, at the same time, they are facing a lot of pressure because of this. For example, Asian American health care workers' stress usually comes from age, marital status, number of kids, unsafety at work as well as discrimination [3]. In order to ensure the medical employees' safety, some researchers find some viable methods: one-way flow of traffic on and off the patient floor, developing a matrix detailing PPE for each work activity and location [4]. A reasonable strategy for retaining healthcare staff is extremely important during the COVID-19 pandemic, which might have some impacts on patients' health conditions, organizational goals, employees' welfare, etc. The most crucial factors, which will affect the staff's retention are bonuses, educational support and stimulus, appropriate working environment and responsibility arrangement, regular communication and so on [5].

2.2 Mental Health Problems and Skin Problems

As a result of prevalence of COVID-19 pandemic, there has been an increasing number of people suffering from potential risks, especially mental health problems. A study proves that COVID-19 pandemic has detrimental effects on sleeping disturbances of adults, relationships between insomnia, and some other factors, such as family income, residence location, gender, etc [6]. Moreover, the pandemic causes severe anxiety and pressure on younger age groups. For instance, many high schoolers are forced to take online courses instead of attending school as usual due to strict rules, which were established by the governments in order to deal with this pandemic [7].

Wearing masks is a quite efficient way to prevent us from being infected by coronavirus virus. However, with talking and breathing, the skin under the mask has to stay in a hot and humid environment for a long time. In such environment, bacteria and microorganisms will become extremely active, causing inflammation in and around the hair follicles and causing a variety of skin problems (see Table 1). In addition, the skin will suffer from long-term pressure as well, which is more likely to appear redness, swelling, and wear. These small wounds are also more likely to be infected with bacteria, leading to inflammation, and eventually form a mask face. Meanwhile, the heat will soften the skin cuticle, damage the skin barrier and let the skin lock water drop, which can cause skin swelling, skin barrier weakened and give bacteria an opportunity to gain nutrition. Furthermore, people with sensitive skins will suffer from contact dermatitis. The part of the skin wearing a mask is prone to gain erythema and papules. If someone is allergic to the material of the mask, this will also lead to red and itchy face, indentation, or compressive tissue damage [8]. Therefore, in this situation, skin care seems to be quite necessary to avoid getting attacked from skin problems. And more and more people start to purchase for skin-care products, which will undoubtfully increase retail sales of personal care stores.

Table 1. Skin biophysical parameters before and after using the mask for 6 hours a day over 1-week and 2-week periods

Variables	Baseline	After 6 hours	P-value	1 week	P-value	2 weeks	P-value
Temperature (°C)	31.77 (±1.19)	33.86 (±0.88)	.000***	31.83 (±1.07)	.000	31.90 (±1.05)	.000
Redness (a*)	12.03 (2.76)	12.85 (±2.54)	.005**	12.18 (±2.34)	.000	12.24 (±2.30)	.994
Pore (mm3)	0.14 (±0.11)	0.15 (±0.12)	.287	0.17 (±0.12)	.032	0.18 (±0.14)	.014*
Roughness (Ra)	5.02 (±1.10)	5.01 (±1.00)	.794	5.11 (±1.28)	.575	5.14 (±1.17)	.247
Elasticity (R2)	0.73 (±0.05)	0.74 (±0.06)	.794	0.71 (±0.05)	.040	0.71 (±0.05)	.117
Elasticity (R5)	1.02 (±0.15)	0.98 (±0.17)	.292	0.91 (±0.13)	.012*	0.94 (±0.11)	.204
Elasticity (R7)	0.42 (±0.05)	0.41 (±0.05)	.215	0.39 (±0.04)	.008**	0.39 (±0.03)	.006**
TEWL (g/h/m2)	18.73 (±5.76)	21.98 (±5.94)	.001***	17.85 (±6.92)	.211	18.32 (±5.40)	.955
Sebum (a.u.)	107.43 (±58.69)	177.72 (±44.42)	.001***	87.05 (±44.68)	.232	103.42 (±64.05)	.575
pH	5.81 (±0.45)	5.62 (±0.51)	.024*	5.76 (±0.38)	.709	5.56 (±0.25)	.048
Acne	2.70 (±3.01)	-	-	3.55 (±3.24)	.037	4.35 (±2.70)	.001**

3. Methodology

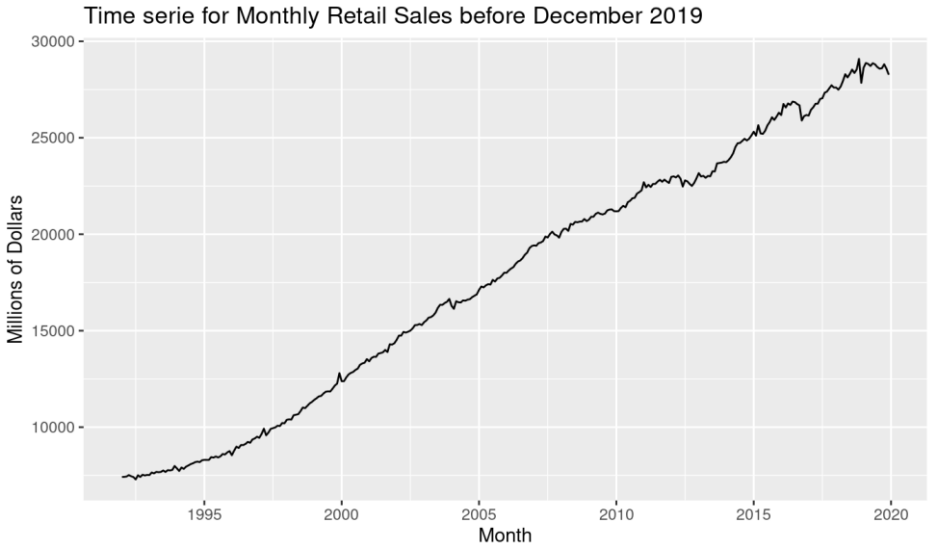
The study by Tandon et al. in 2022 used similar approaches to forecast coronavirus cases in India [9]. This study served a similar purpose to give insight to medical personnel. Researchers built the ACF and PACF of COVID-19 data to propose an ARIMA model. Along with the MAPE, MAD and MSD, the most accurate model is suggested to be ARIMA (1, 1, 1). This best-fit model was used to forecast coronavirus cases in the next month. Then actual cases were compared with the forecasted value, which appeared to be fairly accurate.

3.1 Data

ARIMA models are one of the widely used approaches to time series forecasting, aiming to describe the autocorrelations in the data [10]. ARIMA models were utilized, familiarized and practiced by our research group, to forecast the chosen data and perceive any valuable information contained in the series. Time series released by Monthly Retail Trade and Food Services from U.S. Census Bureau was extracted for our study, especially the Monthly Retail Sales in Health and Personal Care Stores in Millions of Dollars from Jan 1992 to Aug 2022. Since the time series is already seasonally adjusted, confirmed by no fixed and known frequency fluctuations throughout, non-seasonal ARIMA forecasting model was decided to be performed. In addition, daily coronavirus cases in the U.S. reported to the CDC by State or Territory were obtained and statistically transformed by our group into corresponding monthly data. This is imported for a linear regression against our Monthly Retail Sales, aiming to capture any relationship and correlation based on our hypothesis.

From the very first glance, a dramatic and instant drop in Monthly Retail Sales in Health and Personal Care Stores was seen from March 2022. Thus, this paper were particularly interested in how the urgency of a pandemic affects sales and how sales adapted to the pandemic. To better understand the effects and the adaptations, two forecasts were performed: one based on data before 2020

consisting of 336-time series points (BeforeCovid_Data); another is based on the real data set consisting of time series points (Whole_data). Both time series were visualized in R (BeforeCovid_data_ts and Whole_data_ts), as Figure 1 shown.



(a) Before December 2020



(b) Until March 2022

Fig. 1 Visualization of two time series for monthly retail sales (Photo credit: Original)

3.2 Forecasting by ARIMA Model

3.2.1 Forecast for monthly retail sales based on data before December 2019

To understand the effects of the pandemic on healthcare retail sales in the US, forecast of the BeforeCovid_data_ts was generated by the auto.arima ( ) to select a model automatically. A method of making this function consider all the possible models in its search was conducted by introducing the arguments stepwise=FALSE and approximation=FALSE [10].

3.2.2 Forecast for monthly state retail sales for the whole data set

The research group subjectively determined the best non-seasonal ARIMA model for the Whole_data_ts instead of relying on auto.arima R code, aiming to strengthen our knowledge of the logic behind ARIMA models. Before introducing the ARIMA model, the concept of stationarity and the technique of 'detrending' or differencing time series is essential. A non-seasonal ARIMA model can be obtained by combining differencing with autoregression and a moving average model. Non-seasonal ARIMA general modeling procedures is specified as below.

(1) Check the stationary and non-stationary properties of our Whole_data_ts.
(2) Stabilize the variance and mean by logging and determining the degree of first differencing *d*.
(3) Determine the order of autoregressive *p* and the moving average *q*.
(4) Doublecheck the determined ARIMA (*p*, *d*, *q*) with the automated algorithm.
(5) Check the residuals from our chosen model.
(6) Forecast by applying the determined ARIMA (*p*, *d*, *q*).

3.3 Regression

This paper further extended ARIMA to include external variables such as coronavirus cases by introducing dynamic regression models. In this way, this method not only allow for the inclusion of relevant information from predictor variables but also oversee subtle time series dynamics that can be handled with ARIMA models [10]. Regression model refinement and employment of dynamic regression model were performed to exclude influential observations and achieve a more accurate forecast.

4. Empirical Results

4.1 Forecasting Results by ARIMA Model

4.1.1 For monthly retail sales based on data before December 2019

A non-seasonal ARIMA (3, 1, 0) was selected automatically, as Table 2 shown. By comparison of this first forecast and the observed time series, it can be seen that observed values after COVID-19 prevalence deviate a lot from predictions (see Figure 2), even outside its prediction intervals, suggesting the dramatic effect caused by the pandemic and maybe some consequent policy making.

Table 2. ARIMA (3, 1, 0) with drift

	arf1	arf2	arf3	drift
Coefficients	-0.3495	-0.0915	0.0795	62.6047
S.D.	0.0551	0.0585	0.0552	6.4626
sigma^2	log likelihood	AIC	AICc	BIC
26205	-2177.5	4365.01	4365.19	4384.08

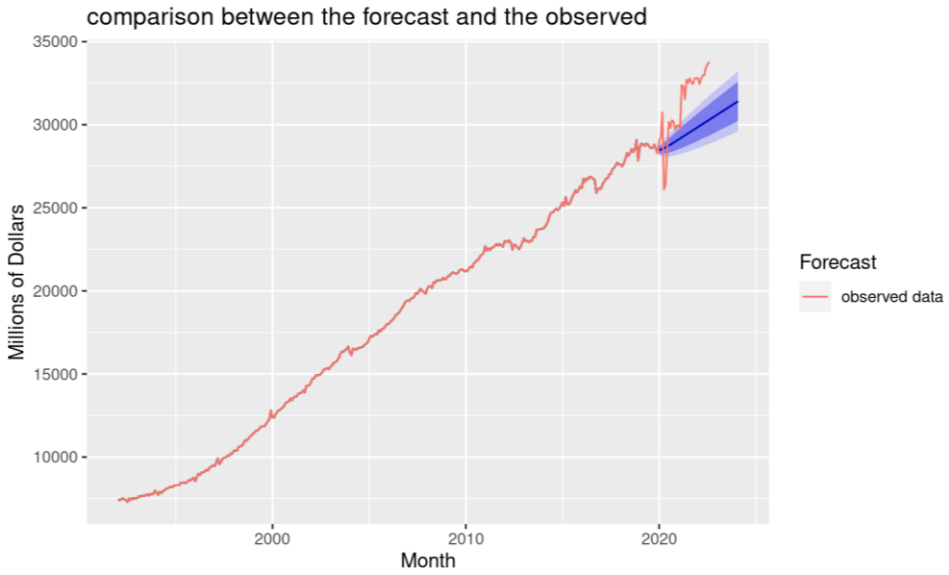


Fig. 2 Comparison between the forecast and the observed time series (Photo credit: Original)

4.1.2 For monthly state retail sales for the whole data set

In Step 1, non-stationary properties were confirmed by looking at ACF, PACF and unit root tests which is a statistical hypothesis test of stationarity (see Figure 3). Both actions suggested that our time series is not stationary: Lags values in ACF decrease slowly, and the test statistic in the unit root test is much more significant than the 1% critical value (in Table 3), indicating that the null hypothesis is rejected. That is, the data are not stationary.

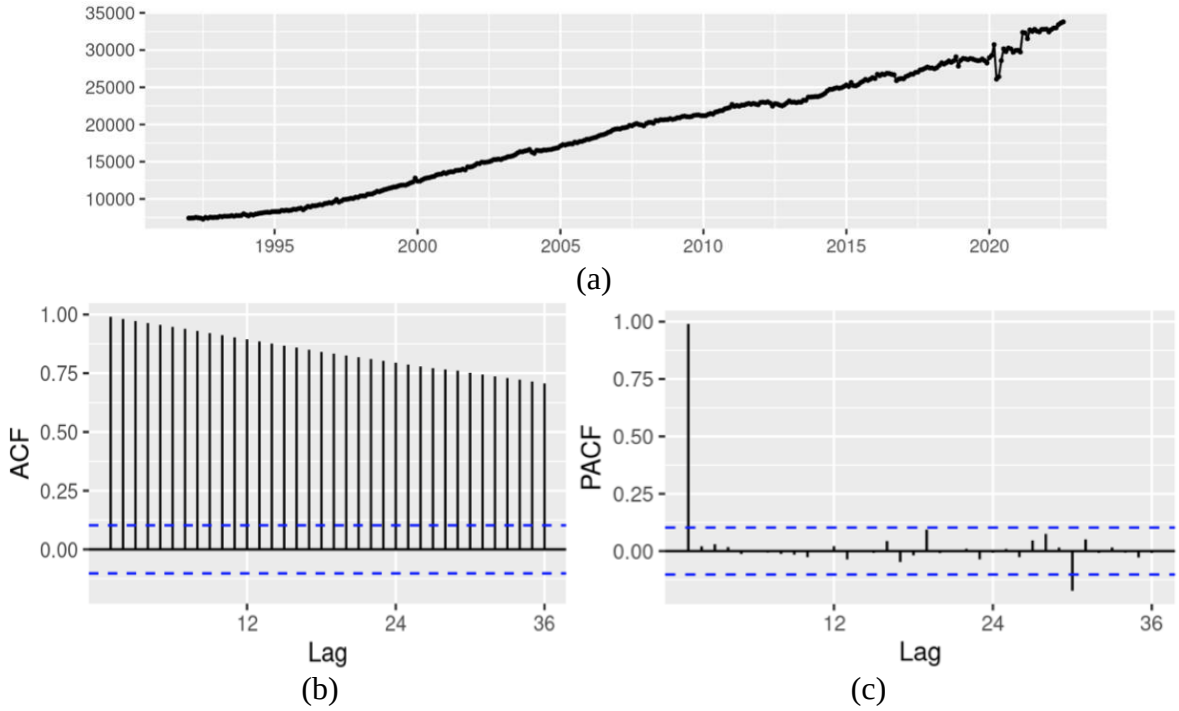


Fig. 3 Evaluation of the non-stationary properties of Whole_data_ts (Photo credit: Original)

Table 3. KPSS unit root test for the Whole_data_ts

Critical Value	Significance level
0.347	10 pct
0.463	5 pct
0.574	2.5 pct
0.739	1 pct
test-statistics	6.1928

In Step 2, to eliminate the increasing trend observed, transformations such as logarithms can help to stabilize the variance of time series, whereas taking differences can help stabilize the mean of a time series. Thus, logarithms of Whole_data_ts was generated first, which reduces the trend, and then the KPSS test was performed to determine the appropriate orders of differencing. The order d=2 was determined, and two orders of differencing of our time series after applying the logarithm were performed and drawn (see Figure 4). Then, the transformed time series' stationary or non-stationary properties were checked again by looking at ACF, PACF and unit root tests (see Figure 5). Both actions suggested that our time series is stationary at the current stage: plots of the transformed time series look much like white noise, being independently distributed; the test statistic is tiny (in Table 4), and well within the range it would expect for static data. That is, the transformed data are stationary.

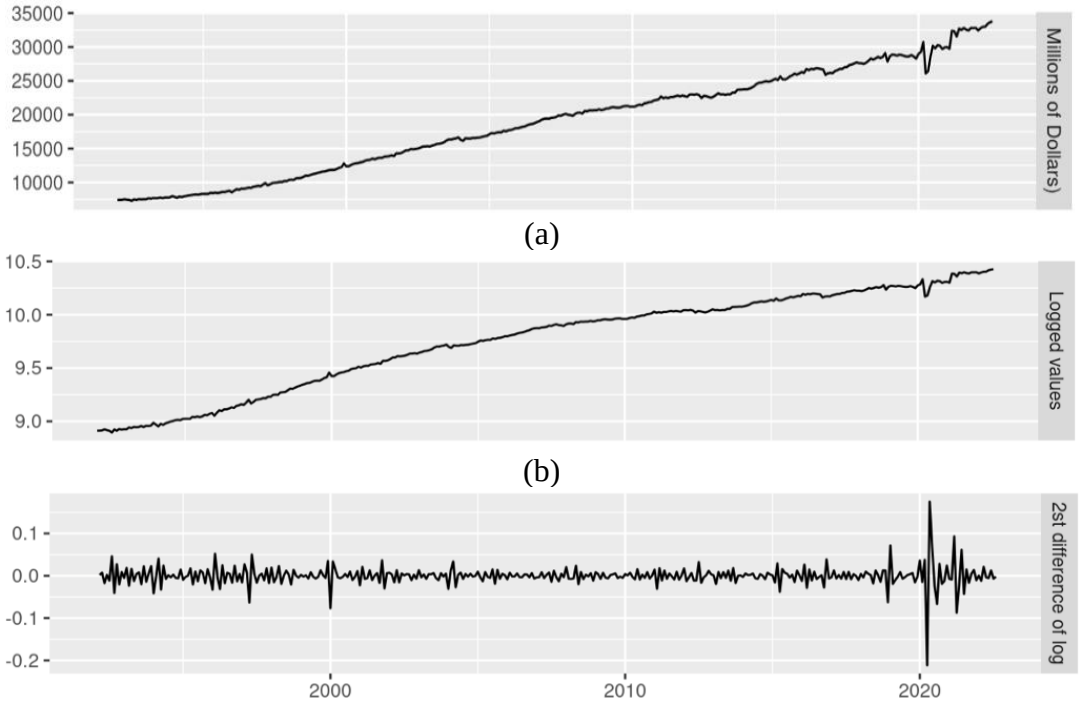


Fig. 4 Gradual stabilization of Whole_data_ts. (Photo credit: Original)

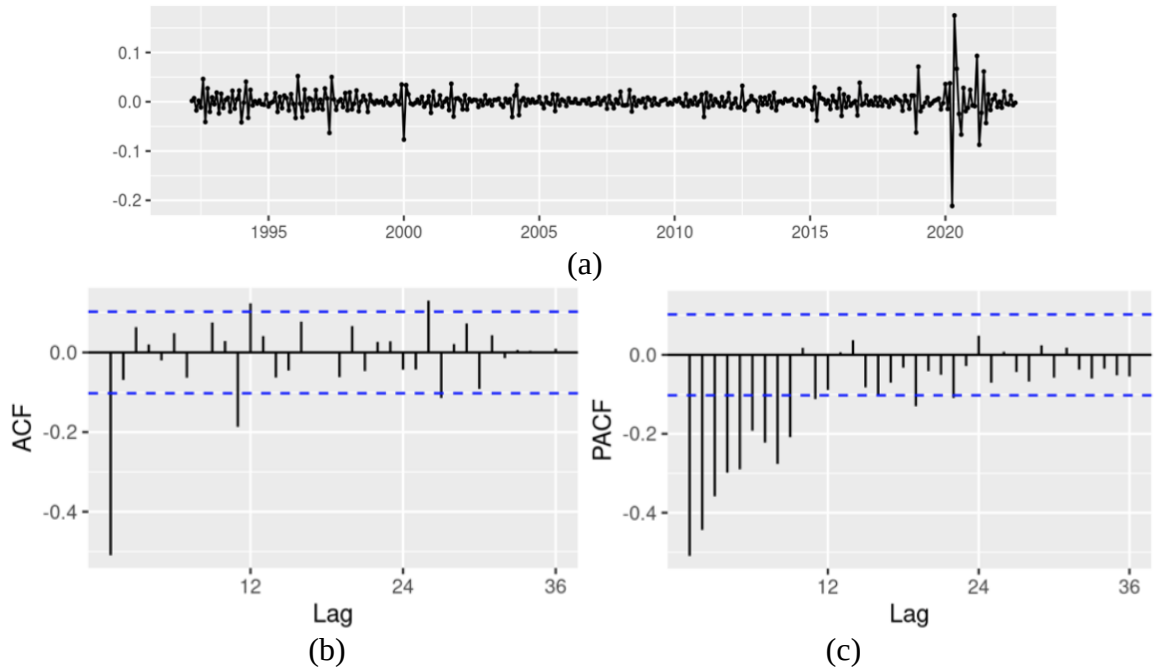


Fig. 5 Evaluation of the non-stationary properties of the stabilized time series (Photo credit: Original)

Table 4. KPSS unit root test for the Whole_data_ts after logging and differencing twice

Critical Value	Significance level
0.347	10 pct
0.463	5 pct
0.574	2.5 pct
0.739	1 pct
test-statistics	0.0089

In Step 3, ACF and PACF plots based on our logged Whole_data_ts were observed and evaluated. ACF can be used to determine the order for MA components, and PACF can be used to determine the order for the AR part. A sudden fall happens after lag 1 in ACF and an exponential change in PACF; thus, our group estimated our q to be 1 and want to try a range of q from 1 to 3 in case to find a better order. From PACF, it can be estimated a sudden fall from lag2, lag3 and lag5. Nine different combinations of ARIMA models were evaluated, and it turned out ARIMA (2, 2, 3) is the best with the least AIC and BIC value, suggesting a model with fewer parameters (less model complexity) but good fitting performance (in Table 5). In Step 4, Auto.arima function works harder by using the arguments stepwise=FALSE and approximation=FALSE. The result was consistent with what subjectively determined, suggesting ARIMA (2, 2, 3) is the best.

Table 5. Evaluation of nine different ARIMA models based on AIC and BIC values

ARIMA model	AIC (2.s.f)	BIC (2.s.f)
(2, 2, 1)	-2078.74	-2063.11
(2, 2, 2)	-2092.61	-2073.07
(2, 2, 3)	-2097.44	-2073.99
(3, 2, 1)	-2086.30	-2066.76
(3, 2, 2)	-2090.89	-2067.44
(3, 2, 3)	-2090.69	-2063.33
(5, 2, 1)	-2089.75	-2062.39
(5, 2, 2)	-2087.92	-2056.66
(5, 2, 3)	-2088.01	-2052.84

Finally, the checkresiduals function performed the evaluation to see if the residuals were independently distributed (see Figure 6). Here, the p-value (0.164) exceeds 0.05, which exceeds the Ljung-Box test, suggesting that the null hypothesis H0 (The residuals are independently distributed) is accepted. Whole_data_ts was performed and shown below is the result (see Figure 7). It can be clearly perceived that one of the limitations is that the confidence in prediction decreases as time goes by.

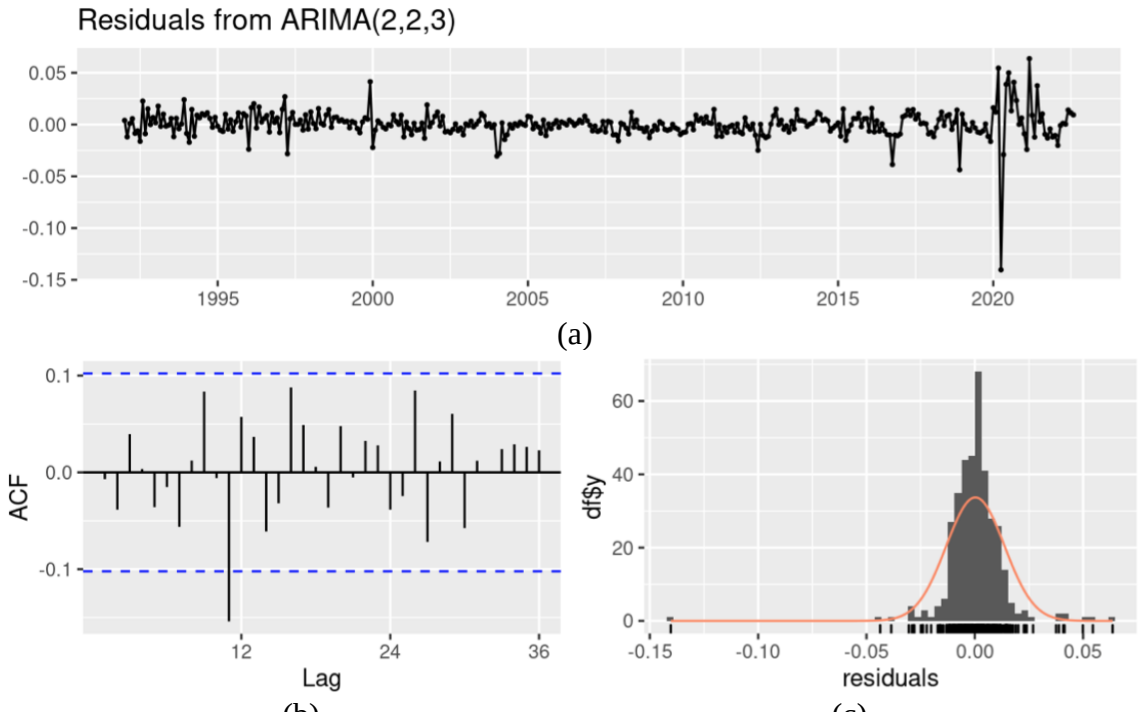


Fig. 6 Evaluation of residuals of ARIMA (2, 2, 3) (Photo credit: Original)

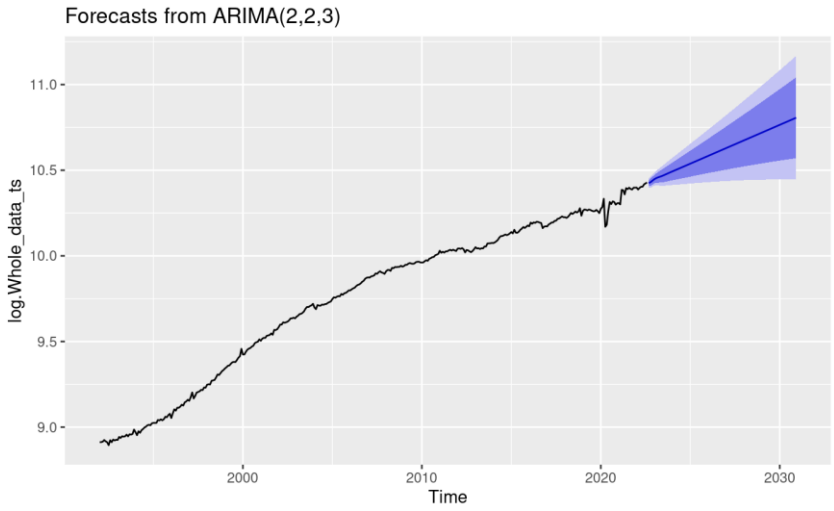


Fig. 7 Forecast by applying the determined ARIMA (2, 2, 3) (Photo credit: Original)

4.2 Regression Results

4.2.1 Initial linear regression

Daily coronavirus cases in the US reported to the CDC by State or Territory were obtained and transformed into logged monthly coronavirus cases, being statistically consistent with our logged monthly retail sales. Parameters of our linear regression model were determined with logged monthly retail sales against logged monthly COVID-19 cases (in Table 6). Our linear regression model was also visualised via the ggplot function (see Figure 8). The fitted line has a positive slope, reflecting the positive relationship between covid cases and retail resales. The slope coefficient shows that one unit increase in log covid cases result on average in 0.01138 units increases in log retail sales. By checking residuals and Residuals vs Fitted plot, it was concluded that our simple linear regression model's performance was not ideal due to the failure of Ljung-Box test statistics (see Figure 9) and a correlation between residuals and the fitted (see Figure 10). Therefore, some refinements to this linear regression model were considered to output a better result, finding a more accurate correlation between logged monthly retail sales and logged monthly coronavirus cases.

Table 6. The linear regression model between logged monthly retail sales and logged monthly coronavirus cases

Intercept	Gradient
10.18525	0.01138

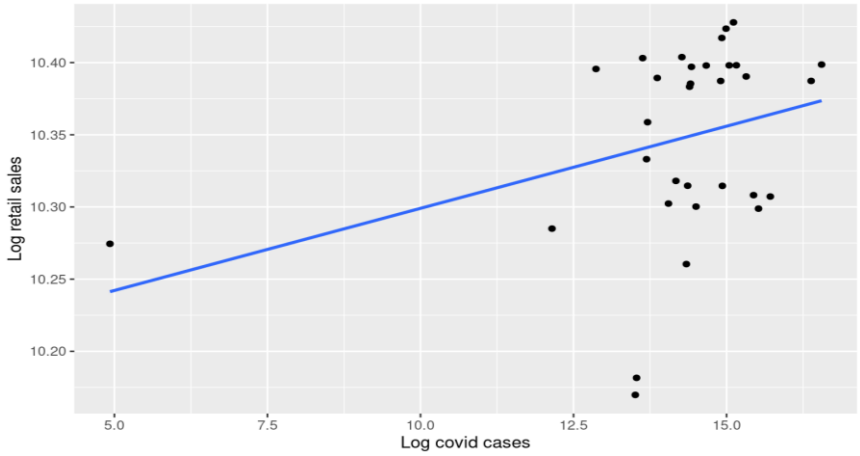


Fig. 8 The fitted linear regression model with a positive slope (Photo credit: Original)

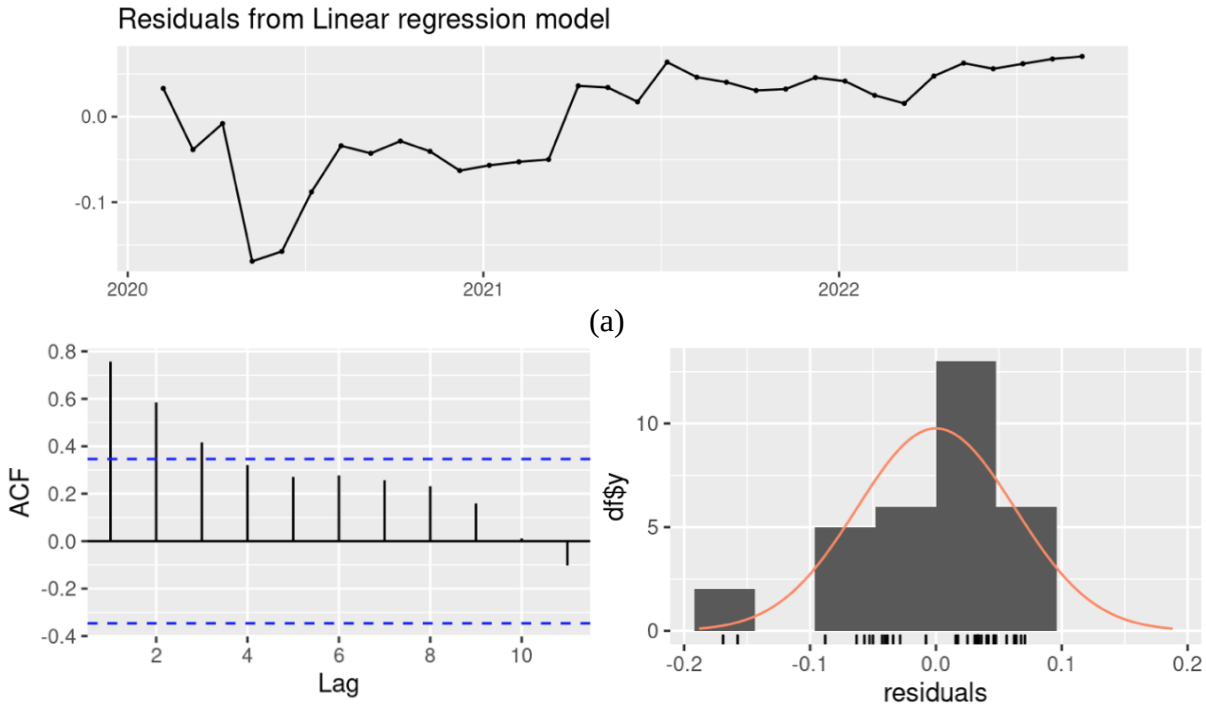


Fig. 9 Results from checkresiduals function (Photo credit: Original)

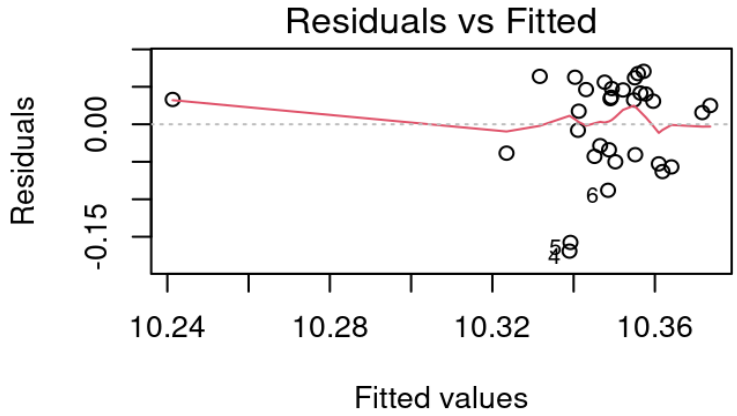


Fig. 10 Correlation between residuals and the fitted values (Photo credit: Original)

4.2.2 Regression model refinement by excluding outliers

Several influential observations were spotted and two of which hugely affect our regression model performance were decided: observations 1 and 5. These two outliers were excluded before applying the linear regression model again (see Figure 11). This time, Ljung-Box test statistics become more significant, and a scattered pattern of points in the Residuals vs Fitted plot can be seen (see Figure 12), suggesting a better regression model for depicting the correlation between logged monthly retail sales and logged monthly coronavirus cases. The slope coefficient of this better-fitted line shows that one unit increase in log coronavirus cases results on average in 0.01747 units increases in log retail sales.

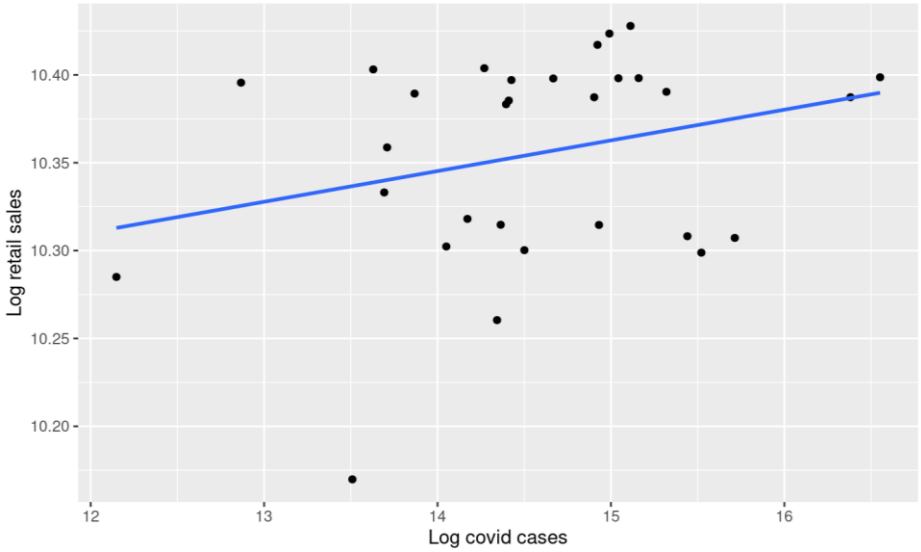


Fig. 11 The refined linear regression model (Photo credit: Original)

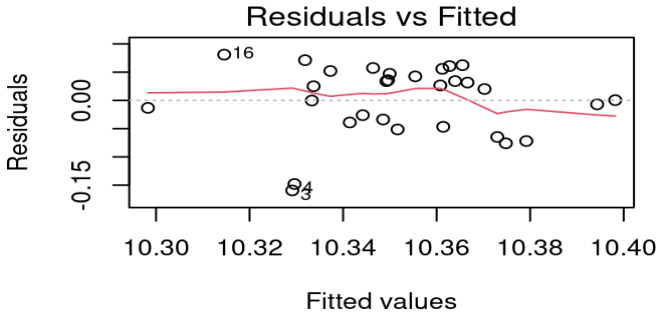


Fig. 12 Correlation between residuals and the fitted values (Photo credit: Original)

4.2.3 Forecast by introducing dynamic regression models

The residuals of our refined linear regression model still show some autocorrelation. Dynamic regression models contained in the ARIMA allow the errors from regression to contain autocorrelation and achieve a more accurate forecast. A regression with ARIMA (0, 1, 1) errors was determined by adding a xreg argument, and its errors resemble a white noise series which is not shown in this paper. A log monthly retail sales forecast from 2020 from regression with ARIMA (0, 1, 1) errors was produced (see Figure 13). In the end, this method not only allow for the incorporation of relevant information from predictor variables but also monitor time series dynamics that can be handled with ARIMA models.

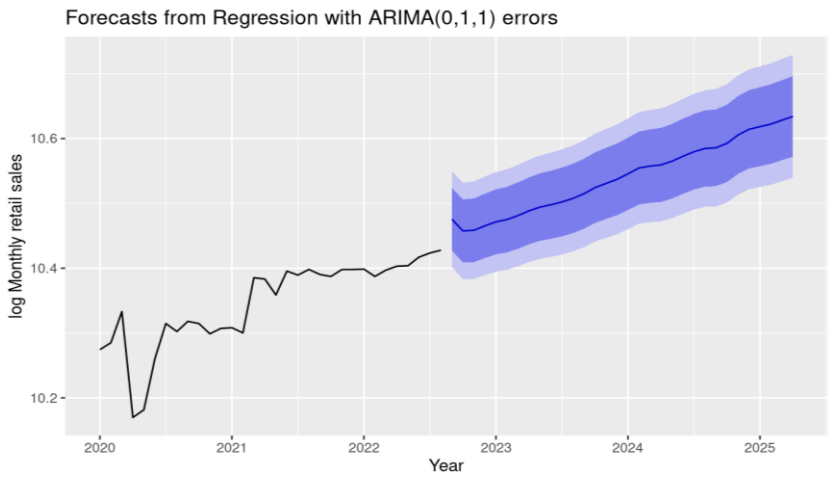


Fig. 13 Forecasts from regression with ARIMA (0, 1, 1) errors (Photo credit: Original)

5. Conclusion

The outbreak of COVID-19 since early 2020 has become a global crisis. Regardless of its fatality, the number confirmed cases keep rising. To help the health and personal care industry better cope with COVID-19 and prepare for any other possible crisis, it is crucial to extrpolate past retail sale and COVID cases. This paper firstly demonstrates some background information under this topic, such as the impact of Covid-19 pandemic on management of health care stores and their staffs, mental damage as well as skin problems, which shows that this issue requires to be solved. Then, in the study of the US Monthly Retail Trade and Food Services time series from Jan 1992 to Aug 2022, it can be determined a non-seasonal ARIMA (2, 2, 3) model to be the best. A positive correlation between logged monthly retail sales and logged monthly COVID-19 cases from 2020 to Aug 2022 was concluded by performing a refined linear regression model. Slope coefficient of this better-fitted line shows that one unit increase in log coronavirus cases results on average in 0.01747 units increases in log retail sales. Moreover, a dynamic regression model was included in the ARIMA to better forecast our time series by containing relevant information from predictor variables like coronavirus cases.

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