





Contents

Executive Summary	2
1. Introduction	2
2. Data Characteristics	5
2.1 Data characteristics of US VMT	5
2.2 Data Characteristics of Producer Price Index -Tire (PPI-Tire)	7
2.3 Data Characteristics of Tire Replacement Shipment (Passenger Vehicle) vs. VMT & PPI-Tire	8
2.4 VMT by U.S. States	9
3. Model Selection, Interpretation, and Forecast	10
3.1 Model Selection & Interpretation	10
3.1.1. Winters' Three- Parameter Exponential Smoothing Method	11
3.1.2. ARIMA Model	11
3.2 Model Evaluation	12
3.3 Model Diagnosis	13
3.4 Model Forecast	13
3.4.1 Tire Replacement Model Interpretation	13
3.4.2 Tire Replacement Forecast	14
4. Conclusion & Recommendation	19
Appendices	21
Appendix A: Data Characteristics	21
Appendix B: Winters' Method & ARIMA Model	21
Appendix C: Error Measurement	23
Appendix D: Model Diagnosis	23
Appendix E: Forecast the Tire Replacement, PPI-Tire, and Goodyear Tire Replacement (Passenger) Market Share	25
Reference	28



Executive Summary

The premier U.S. tire producer, Goodyear Tire & Rubber Co has always been the top seller in the passenger tire replacement market. In recent years, both weakening demand and rising raw material costs presented Goodyear with significant challenges. Overproduction has become a crucial issue. To tackle this forecasting problem, Goodyear assigned us, the Operation Analytic Team, to conduct research and provide informed recommendations to executives. As Tire Replacement is closely associated with vehicle miles traveled¹ (VMT), it is essential to investigate historical records to accurately forecast the future market. In order to identify an optimized model to increase the reliability and precision of replacement tire passenger vehicle and regional demand so to properly allocate its resources among different plants, our team adopted different statistic approaches and concluded that the ARIMA model had the most precise prediction. The total U.S. vehicle miles traveled from 2018 to 2020 will be 9,888 trillion miles, and the total passenger tire replacement market for the next 3 years is forecasted to be 632 million units. With Goodyear's 13 percent share of the passenger tire replacement market, its estimated total production will be 82.16 million units. Given the proportion of VMT for each state, the production for Goodyear's six factories producing passenger tires in 2018 should be 2.57, 2.98, 5.33, 8.6, 3.9 and 3.75 million units, respectively. We also suggest decision makers be cautious in adopting the projected demand to control its production, inventory and cash flow.

1. Introduction

Goodyear Tire & Rubber Company (GT) is one of the world's leading tire manufacturer. With a business presence in both the U.S. and global market, Goodyear develops, manufactures, markets and distributes tires for most of the applications. The business is comprised of two distinct sectors: Original Equipment (OE) tires, which are the tires for new vehicles applied directly by automobile manufacturer, and Replacement Tires, which are for passenger vehicle owners, sold through dealerships, chain stores, service

¹ The vehicle mile traveled refers to the number of miles traveled by vehicles of all types on public roads and streets in a specific period.



stations, department stores, and wholesalers. Generally, replacement tires of all types accounted for a large proportion of U.S. tire consumption, and most of the growth in tire sales come from the replacement tire market. In 2016, 71% of Goodyear's revenue came from Replacement Tire, while OE accounted for only 29%.² The U.S. is the biggest market for Goodyear's Replacement business, with 33.6% unit sales derived from this market³.

The Replacement Tire market is comprised of five sections, including passenger, truck, light truck, off the road and farm. Among different types of vehicle tires for replacement, passenger vehicles accounted for \$24.6B of Goodyear's revenue in 2016, constituting 65% of the total U.S. replacement market. Although total tire sales were less than main competitor Bridgestone America, Goodyear was actually the leading tire manufacturer in the passenger vehicle sector, accounting for 13% of the market share in 2016.⁴ However, in recent years, the replacement tire demand was declining, and factory production capacity had increased by additional installments. Goodyear experienced decreases in both unit sales and income for replacement tires, despite inventory continuing to increase. In 2017, Goodyear's inventory level remained very high in wholesale distribution centers⁵ with \$2,179 million of inventory of finished goods at the end of the year, which represented a 15% increase compared to 2015.

Higher inventory levels incurred a waste in logistics as well as inventory cost, ultimately reducing the gross profit margin. This problem stemmed from an alarming phenomenon involving Goodyear over-forecasting the demand for their products over the past two years (2016-2017). Since Passenger Vehicle Tire Replacement is the most important business to Goodyear and has become its strategic focus, company Executives aimed

² Goodyear's 2016 Annual Report, from <https://corporate.goodyear.com/>

³ Goodyear's 2017 Annual Report, from <https://corporate.goodyear.com/>

⁴ "What to expect in 2017: Despite mixed signals, there is a lot to be optimistic about", Bob Ulrich, Jan 2017 Modern Tire Dealer, from <https://www.moderntiredealer.com/>

⁵ Goodyear cuts 2017 forecast amid higher raw material costs, Arunima Banerjee, Oct 2017 from <https://www.reuters.com/>



to re-evaluate the production level and supply chain distribution networks. Meanwhile, the U.S Tire market is changing with higher material cost and higher tire price. Therefore, it is crucial for Goodyear to adapt to the market demand to produce at a proper level.

As an analyst team within Goodyear's Operation and Supply Chain Department, our goal was to re-estimate the market demand for passenger vehicle tire replacement for the next three years. With such adjusted forecast demand, we correctly forecasted the production volume of Goodyear Consumer and Passenger Tire plants to assist decision makers in executing an efficient production plan while reducing waste, inventory and delivery cost in the following period.

Historically, the replacement tire market volume was closely related to VMT and Producer Price Index (tire). The model prediction revealed VMT data over the years could explain almost 96% of the variation in tire replacement shipments (See Appendix E). Currently, Goodyear uses the public forecasted VMT that is drawn by Winters Method. Although this method is robust, it always exaggerates the VMT, which led Goodyear to over-estimate the replacement tire market. One of our key findings in this analysis was the validation of a better model---ARIMA. This model was better fitted with historical data than Winters Method, thus reducing the probability of over-forecasting. Moreover, we concluded that from 2018 to 2020, Goodyear should produce a total of 27.10M, 27.35M and 27.60M tire units respectively in its Passenger Vehicle sector. At this moment, Goodyear is producing passenger tire and consumer tires in six factories, including Akron - Ohio, Danville - VA, Gadsden Alabama, Lawton - Oklahoma, Fayetteville - North Carolina and Tonawanda - New York. We suggested that in order to minimize the delivery cost from manufacturing plants to distribution centers in each state, Goodyear should allocate their resources in six factories, producing passenger tires 2.57, 2.98, 5.33, 8.6, 3.9 and 3.75 million units respectively in 2018.

Our report is organized into four main sections. **Section 1 - Data Characteristics** describes and visually depicts several sources of historical data, which will be used to



examine, forecast, and illustrate their changes across time. **Section 2 - Model Selection, interpretation and forecast** explores a better model that generated desirable VMT estimation with model evaluation and diagnosis and interprets finding in business sense. **Section 3 - Conclusion and Recommendation** summarizes key finding and presents recommendations for Goodyear Executives to apply the key finding into Tire production and distribution. **The Appendices A-E** contain all the statistical data that support our argument.

2. Data Characteristics

Empirically, replacement tire demand is associated with the mileage people traveled and producer cost for tires. The historical monthly U.S. Vehicle Miles Traveled [VMT] (in millions) dataset and Producer Price Index for tire are available at Federal Reserve Bank of St. Louis. Meanwhile, we collected the replacement tire data for 1975 to 2017 from different sources. In this section, we explored the relationship among them and visually depicted the trend and features of every dataset.

2.1 Data characteristics of US VMT

VMT was calculated by vehicle type and roadway functional class by each state. The state-wide data were then aggregated into a national level. The time series data of VMT in the U.S. beginning in 1970 and ending in 2017 is presented in Figure 1 below. Table 1 in Appendix A briefly presents descriptive statistics for the monthly VMT.

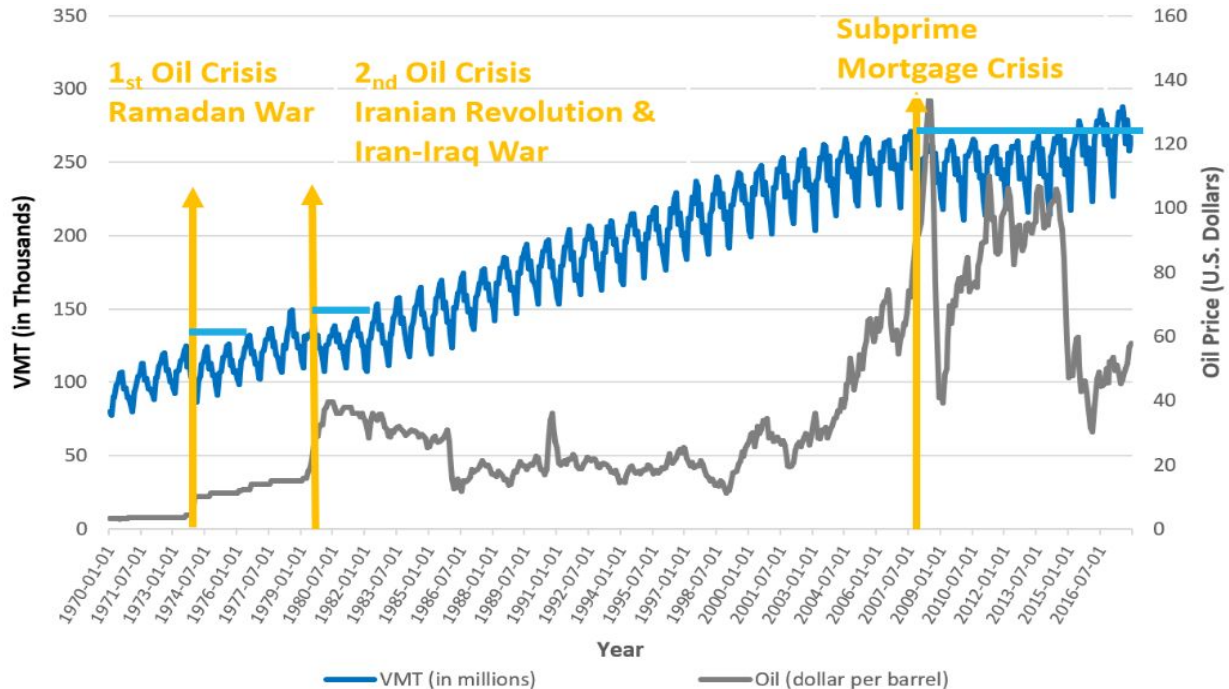


Figure 1: U.S. Vehicle Miles Traveled (in millions) from 1970 to 2017

VMT began with the lowest 77,442 million miles in Feb. 1970 and almost quadruples at 287,358 million miles in Jul. 2017. From the above graph, we determined that although VMT displays a general upward trend from 1970 to 2000, it plateaued after 2001. From the 1970s to the beginning of the new millennium, VMT maintained consistent growth with a compound annual rate of 3.40%. However, the compound annual growth rate was merely 1.51% from the new millennium to 2017.

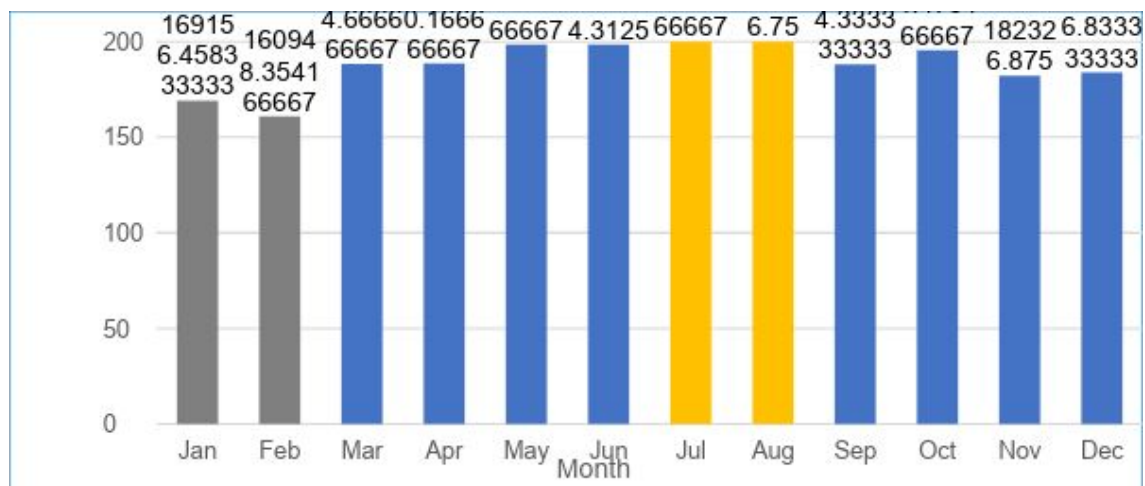
VMT can be impacted by many demographic and socioeconomic factors such as population, level of income, unemployment rate and fuel price. Many key VMT developments can be attributed to the fluctuation of gas prices. There were several VMT drops coinciding with oil price hikes. For example, VMT first dropped in 1973 when oil prices quadrupled, leading to an economic stagflation in the U.S. This was followed by the 1979 oil crisis that originated in Iran, which led to spikes in the same period and VMT decreased pronouncedly. The 1990s witnessed the longest period of steady growth in U.S. recent history, and VMT enjoyed consistent gains, showing somewhat steep and even exponential momentum. However, the Sept. 11, 2001 terrorist attacks brought this period to an end and oil price were driven sky high. Several years later the



subprime mortgage crisis in 2008 contributed to a global financial crisis, causing oil prices to soar. VMT growth leveled off after that and regained its upward trajectory again after 2014 due to the gradual economic recovery. However, there were also some unique observations that seemed counterintuitive to many of our findings. For example, oil prices did increase in 2003 but the VMT seemed to be unaffected. This may be explained by a minor increase in population growth rate at the same time. Evidently, plenty of factors can explain VMT and many have either strong or indiscernible correlation with each other, making the forecast process complex and difficult. Therefore, we used another method instead of regression to explain the trend of VMT.

There are several key VMT observations over the past 48 years:

The first observation was the prominent seasonal pattern. Figure 3 below shows the average VMT per month across time. Based on the graph's visual depictions, monthly variation is evident in VMT, which usually peaked during summer season and troughed in the winter seasons. A seasonal index⁶ was obtained to better comprehend this variation (see Appendix A for details). It showed that compared to the annual average level, people usually drove 8%-9% more in July and August, and 10%-15% less in January and February.



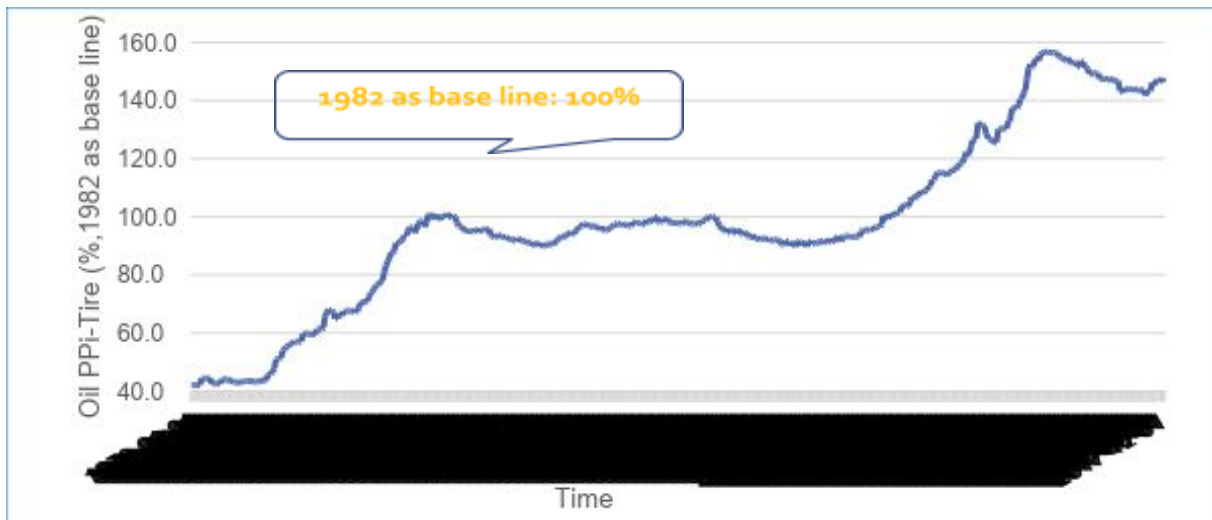
⁶ Seasonal index is a measure of how a particular season compares with the average season.

**Figure 2: Monthly Average U.S. Vehicle Miles Traveled (in millions) from 1970 to 2017**

The second observation is the slight cyclical pattern. The U.S. economy experiences downturns approximately every 10 years. However, VTM seems not to be affected considerably by the respective recessions. Though we observe 2 temporary plateaus around 1979 (Energy crisis) and 2008 (Financial crisis), VMT recovered very quickly afterward and continue to increase.

2.2 Data Characteristics of Producer Price Index -Tire (PPI-Tire)

Designating 1982 as the baseline (100%), the series illustrates how the selling prices had inflated overtime. As seen on Figure 3, annual PPI-Tire had fluctuated from 1982 to 2005 in a range of 90-100%, before surging significantly to over 150% during the financial crisis. We will examine how PPI-Tire related to the Tire demand in the next part.

**Figure 3: Fluctuation of PPI-Tire from 1975 to 2017 (%)**

2.3 Data Characteristics of Tire Replacement Shipment (Passenger Vehicle) vs. VMT & PPI-Tire

The following graph depicts annual tire replacement shipments in the passenger vehicle market (from 1975 to 2017) and indicates the trend of U.S. tire demand over 32 years.



Though experiencing declines in certain years (1979, 2001, 2009 and 2011), tire replacement shipments had increased significantly at an average annual growth rate of 1.25% and were strongly correlated with annual VMT data.

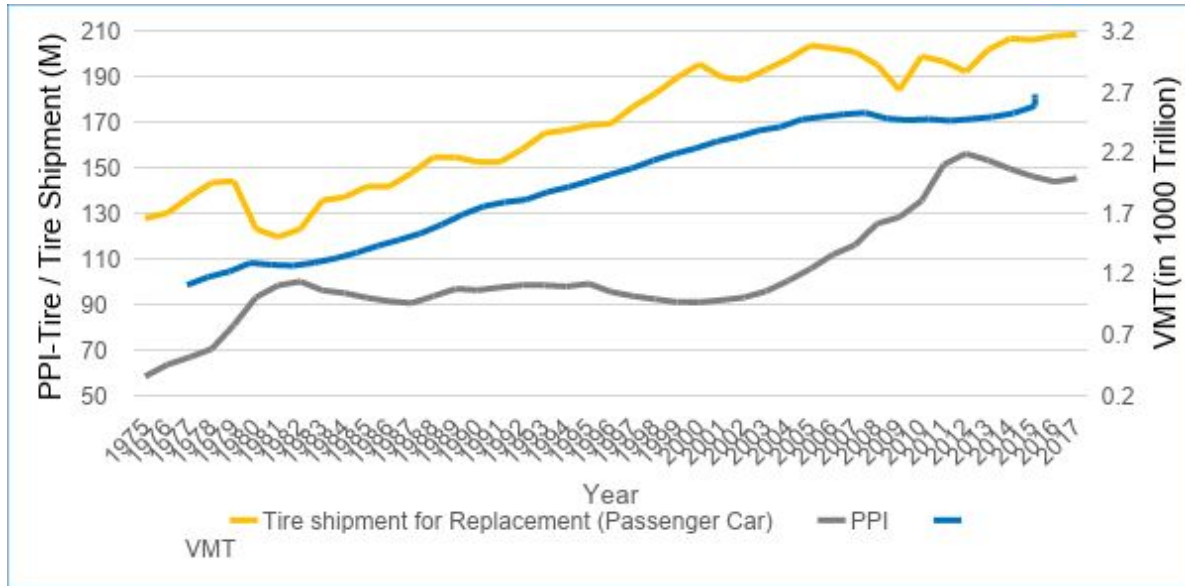


Figure 4: Tire Replacement (Passenger) vs. PPI-Tire & VMT from 1975 to 2017

We further computed the correlation between these two variables, and the statistic results verified our informal observation (see Appendix A). Such validation provided us the basis to use VMT and PPI as the main variables to forecast the tire demand for the whole U.S. market, and we will verify the model in a later section.

As visualized in Figure 4, PPI and Tire Replacement demand shown fairly contradict direction over the years. For instance, in the economic recession in 1979 and 2008, PPI rose dramatically while Tire demand declined. In the period from 1982-2005, while PPI was fairly stable, tire demand kept increasing. According to the statistic result, these two datasets had a positive correlation of 0.69, implying that there might be a linear relationship between them (see Appendix A). Therefore, we will use VMT and PPI-Tire to explain the variability of Tire replacement demand and forecast the total demand in the U.S. for the next three years.

2.4 VMT by U.S. States

The level of VMT varied among the 50 U.S. states depending on their respective populations and other factors. Unsurprisingly, California has the biggest contribution to the total U.S. VMT with 10.71%, followed by Texas and Florida with 8.55% and 6.69% respectively⁷. People in East Coast states such as New York, Ohio, North Carolina drive fairly common due to its level of urbanization and the dynamics of the state-wide economies. Therefore, though being small, VMT in these states accounted for more than 3% of the total. On the other hand, states in the North and Mid-West had remarkably small contributions to national VMT, with less than 2% for each state. (as shown in Figure 5).

With the assumption that VMT proportions for each state remain constant in the near future, we utilized this proportion data to forecast VMT at state level for the next three years. Therefore, we can optimize the production operation among different factories to reduce transportation costs and better allocate inventory distribution as well.

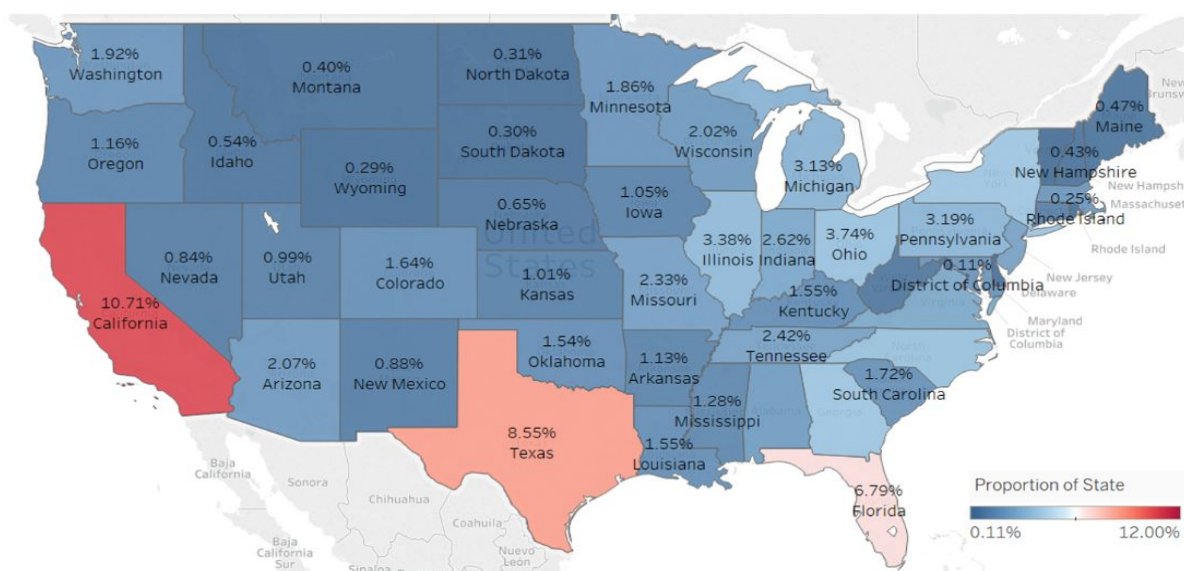


Figure 5: Contribution of each U.S. state (except Alaska) to national VMT in 2016 (%)

Although the charts and tables were suggestive, they are not sufficient enough to capture the underlying track of all variables. The next section explored these relationships more rigorously through statistical analysis.

⁷ We calculate the proportion of each state based on the VMT data for each state in 2016.



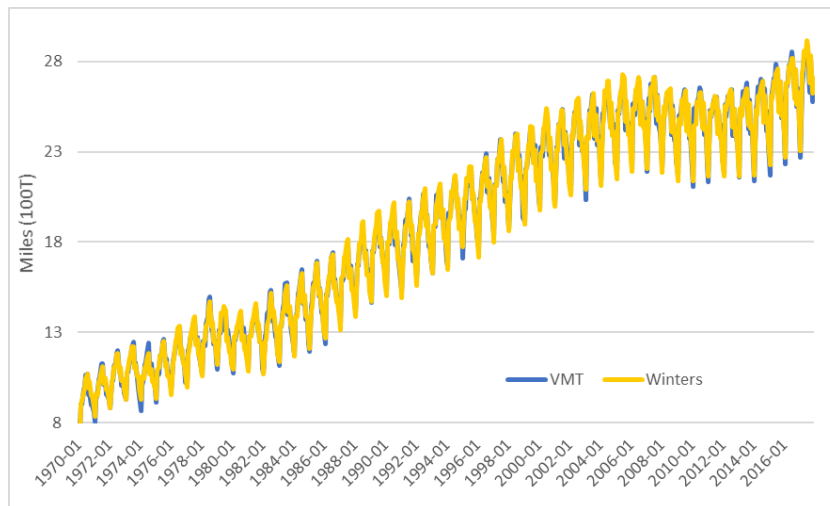
3. Model Selection, Interpretation, and Forecast

We aimed to find a model that can accurately reflect VMT progress and in turn estimate the tire demand. Such model should minimize the forecasting error and improve the predicted values. In this section, we will discuss how we compare the current model Goodyear is using and deduce the best model to predict the VMT and forecast tire replacement demand.

3.1 Model Selection & Interpretation

As described in the data characteristics, the VMT displayed an upward trend with strong seasonal and mild cyclical feature. Both Winters Method that was adopted by Goodyear and our recommended ARIMA model can effectively interpret data with such features. We begin the introduction of model selection with Winters Method.

3.1.1. Winters' Three- Parameter Exponential Smoothing Method



As Figure 6 shows, Winters' Method produces the values that fit the actual data. However, it can be over-forecasted (See Appendix C).

Figure 6: Winters Method plot for VMT, 1975 ~ 2017 (in 100 trillion)

The Winters' Model that captures both trend and seasonal pattern can be expressed as follows:

$$\hat{y}_t = (L_{t-1} + T_{t-1}) S_{t-p} \quad [\text{Equation 1}]$$

where L as level, T as trend, S as seasonality. Winters Model detail is in Appendix B.



3.1.2. ARIMA Model

A seasonal ARIMA model is a statistic technique that combine both non-seasonal and seasonal factors in a multiplicative model, which can be expressed as follows:

$$ARIMA(p, d, q) \times (P, D, Q)_S \quad [\text{Equation 2}]$$

Where p =non-seasonal Autoregressive order, d =non-seasonal differencing, q =non-seasonal MA order, P = seasonal Autoregressive order, D =seasonal differencing, Q =seasonal MA order, and S =time span of repeating seasonal pattern.⁸

Appendix B provides a detailed explanation on the Seasonal ARIMA.

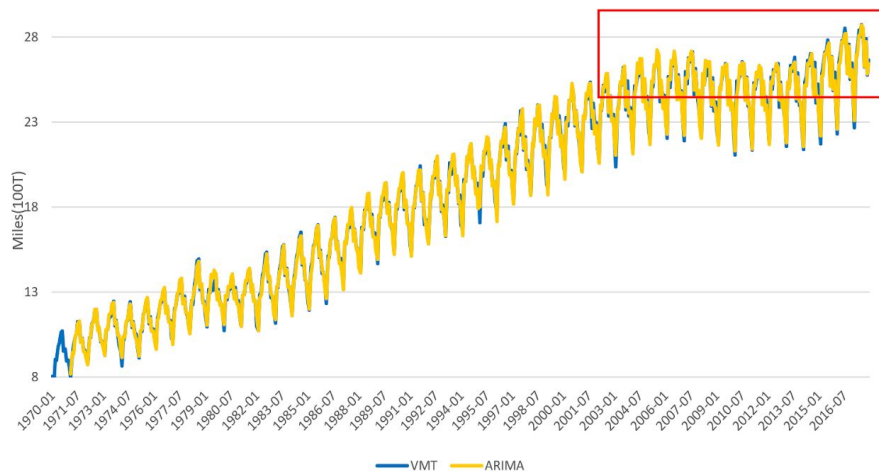


Figure 7: Seasonal ARIMA plot for VMT (in 100 trillion)

We finally identified the $ARIMA(2,1,1) \times (2,1,1)_{12}$ as the appropriate technique that fits the data. Figure 7 shows that the ARIMA model precisely matches the actual data.

Apart from the visualization of the model against the actual data, we evaluated our model through statistical measurement in the next section.

3.2 Model Evaluation

According to the above graphs, both models capture the tendency effectively. However, compared to the Winters' Method, the ARIMA model fits better with smaller error. We applied an internal forecast method to compare the models. First, we run the ARIMA model with the full 576 records to obtain a **full model**; Second, we removed the data of last 12 records (year 2017) to test the first 564 records to obtain a **fitted model**; Third,

⁸ Seasonal ARIMA models, The Pennsylvania State University, <https://newonlinecourses.science.psu.edu/stat510/node/67/>



the fitted model was then used to forecast the removed 12 records, of which the results were called **internal forecast**.

With the output of the full model, fitted model and internal forecast, we evaluate Winters' Method and ARIMA through several metrics, including Mean Squared Error (MSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Deviation (MAPD) (Appendix C Table C-1). All of these are key indices for comparison between the models. The smaller the index is, the better such model fits the data. We noticed that all indices for the seasonal ARIMA model are less than those of the Winters' Method in regards of full records as well as the fitted and internal forecast versions. As a result, we infer that the ARIMA model fits the dataset best, so we can apply it to forecast VMT. We further verified our decision through a diagnosis test on the residuals.

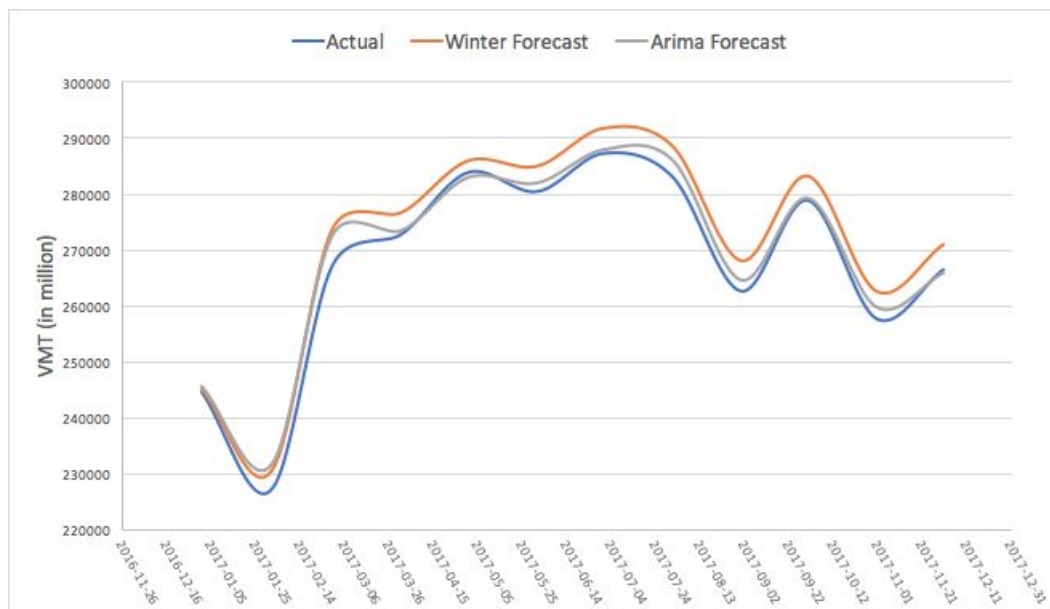


Figure 8: Comparison in forecasting VMT in 2017 between Winter and ARIMA methods.

3.3 Model Diagnosis

To further consolidate our model, we perform several informal and formal tests to verify that the differences between the fitted value and actual value (called residual) meet the underlying requirements (see Appendix D for the details of the underlying assumption). To our satisfaction, the residual passed the test of linearity, constant variance,



independence and normality. Therefore, the model can be applied in computing the potential VMT and Tire Replacement Demand for the next three years. The next section will introduce how we deduce such estimation.

3.4 Model Forecast

3.4.1 Tire Replacement Model Interpretation

After trying several statistic techniques to test the most significant variables and improve model precision, we conclude the transformed log regression model fits the actual data best. It is expressed as follows:

$$\text{Tire Replacement} = 117.567 + 5.1E-05 * \text{VMT} - 33.9813 * \text{Log (PPI-Tire)} \quad [\text{Equation 4}]$$

For detailed explanation and interpretation of this model, please refer to Appendix E.

We briefly summarize our results and interpret our findings:

- For constant 117.567: this is the average tire replacement demand when all the other independent variables are zero. Because zero is outside the range of our collected data, so the constant is meaningless in this case context.
- For coefficient 5.1E-05 of VMT: For each additional million in the VMT, tire replacement unit increase on average by 5.1E-05 million unit.
- For coefficient -33.9813 of Log (PPI-Tire): One percent increase in PPI-Tire is associated with a 0.34 million decrease in Tire Replacement.

3.4.2 Tire Replacement Forecast

Given the above model for VMT and equation for Tire Replacement, we forecasted tire replacement for Goodyear through following four processes:

Step 1: Use ARIMA Model to Predict U.S VMT

We use the ARIMA model as discussed in Model Selection Section to determine the predicted VMT in next 3 years. The Figure 9 with detailed table below shows forecasted annual VMT in three scenarios (Expected, Conservative and Aggressive) with 95%



confidence level⁹. The actual VMT will vary between the minimum and maximum bounds. With such forecasts, we can estimate the replacement tire demand in next three years.

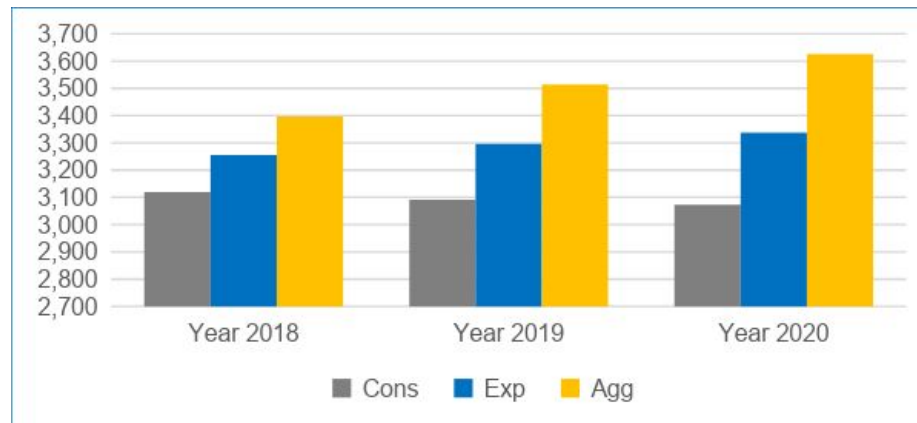


Figure 9: Predicted U.S. VMT (in thousands) from 2018 to 2020 for Varying Scenarios

Step 2: Use Forecasted VMT to Predict U.S. Tire Replacement and Goodyear Tire Replacement

We use the aforementioned regression model to determine the U.S. tire replacement for the next three years (see Appendix E for details). To fit and forecast PPI-Tire, we found the Winters' Method is the best model (See Appendix E for details). Our prediction indicates that PPI will continue to grow to 145.33, 145.41 and 145.49 in 2018-2020 respectively (Appendix E, Table E-2).

Having forecasted VMT and PPI-Tire, we then calculated the total tire replacement in passenger vehicles sector in the next three years (Appendix Table E-3) to be 208.6 Million, 210.7 Million and 212.7 Million units respectively. Goodyear can expect annual growth rates of 0.15%, 0.985% and 0.987% in the period.

As mentioned in the Introduction Section, Goodyear is accounting for 13% market share of passenger tire replacement market. With the assumption that Goodyear market share

⁹ The width of the confidence interval shows how certain we are about the true figure in the population, and is stated as a plus or minus (in this case, +/- 5) and is called the confidence interval.



is stable in the next 3 years, we estimate that the tire units that Goodyear can sell in 2018-2020 are 27.1 million, 27.4 million and 27.6 million units respectively. The following graph show our estimated production output that Goodyear should follow to meet the market demand.



Figure 10: Goodyear's Replacement Tire Shipment vs U.S. Total Market Demand (historical 2015-2017 & forecast 2018-2020)

Step 3: Forecast Tire Replacement Demand by U.S States

Due to the differences in population, unemployment rate and other social and economic factors across the country, VMT level varies among these states. As a result, the tire replacement demand also varies sharply. From Goodyear's perspective, it is critical to understand this difference to accurately allocate tire inventory among our wholesale distribution network, including reducing inventory cost and shipping expenses. Based on VMT data by states in 2016, we can estimate the contribution of each state to the total VMT as well as Tire Replacement. We also observe that the variation in Total VMT already explains 96.3% of the variation in Total Tire Replacement (See Appendix E). Such observation forms the basis for us to apply VMT contribution on Tire replacement contribution by States.

The map below (Figure 11) illustrates the local tire replacement demand in the next three years for each state, which strongly follows the VMT contribution. From this map,



California, Texas and Florida are the states that possess the biggest demand for tire replacement. From the distribution of degree of colors that represent the level of demand in each state, Goodyear can allocate its resources and supply more accurately among different regions.

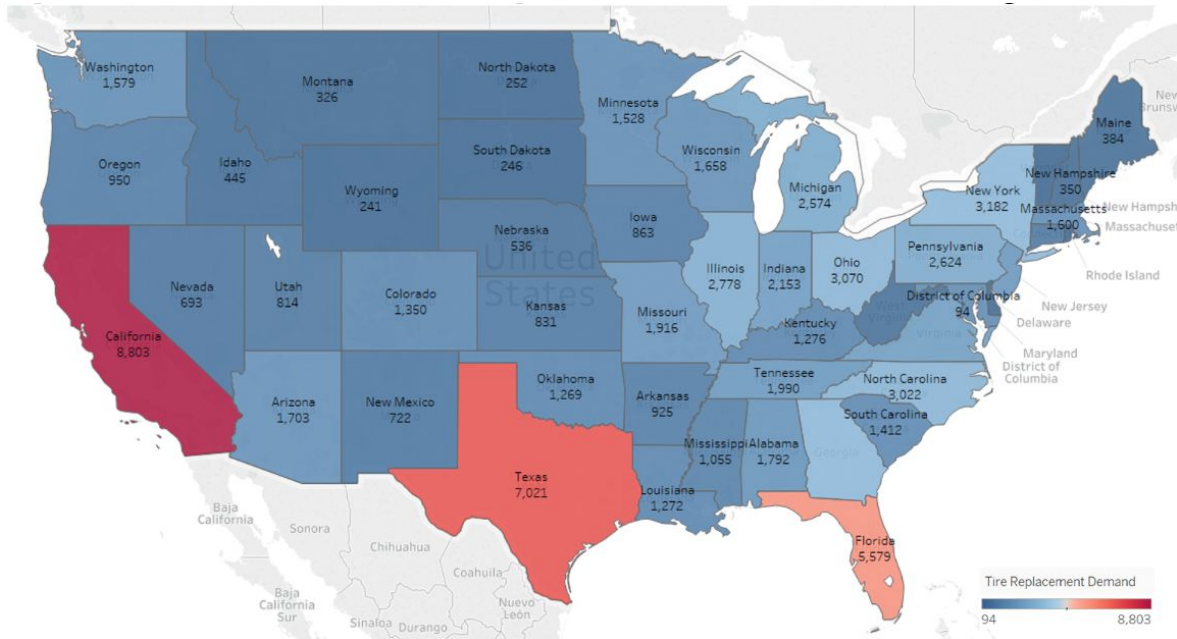


Figure 11: Goodyear Tire Replacement Market by States (except Alaska, in millions) (2018 – 2020)

Step 4: Estimate the Production Allocation among Goodyear Factories.

Currently, Goodyear is producing tire replacement for passenger vehicles in six factories as shown in the following table and map.

Code	Address
Headquarter	200 Innovation Way, Akron, OH
Factory 1	1901 Goodyear Blvd, Danville, VA
Factory 2	922 E Meighan Blvd, Gadsden, AL
Factory 3	1 SW Goodyear Blvd, Lawton, OK
Factory 4	2000 US-24, Topeka, KS
Factory 5	10 Sheridan Dr, Tonawanda, NY



Figure 12 : Goodyear Factory Location (for Passenger Tire) with detailed address



Tire consumes a lot of space when shipping. As the result, the cost incurred from tire shipping from manufacturing plants to distribution centers in the states can be tremendous in comparison with other expense such as tax and labor cost. We suggest Goodyear allocate resources to each factory based on the minimum geographical distance between the factory and each state. Tire demand in each state is assigned to a specific plant to help it achieve the shortest distance from the state to six plants. This way, Goodyear can minimize the shipping route, thus reducing the tire transportation cost. Our computation as shown in Figure 13 indicates that Goodyear factory 3 in Oklahoma should produce for the West and South-West market while Factory 4 in Kansas should serve the Mid-West market; Factory 1 and 2 in Virginia and Alabama should be configured for the South-East region, while headquarters in Ohio should be responsible for only three states – Indiana, Michigan and Ohio.

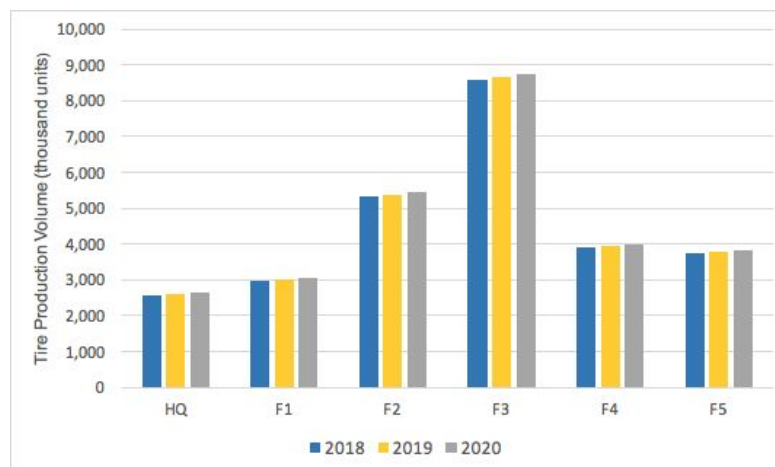


Figure 13: Total Tire production volume by Each Goodyear Factory (2018-2020)

An estimated total production for each factory in the next three years was also obtained using this approach (Figure 14, more detail in Table E-7). Unsurprisingly, Factory 3 in Oklahoma should operate at the largest production volume and Headquarters in Ohio should produce the smallest volume of tires.

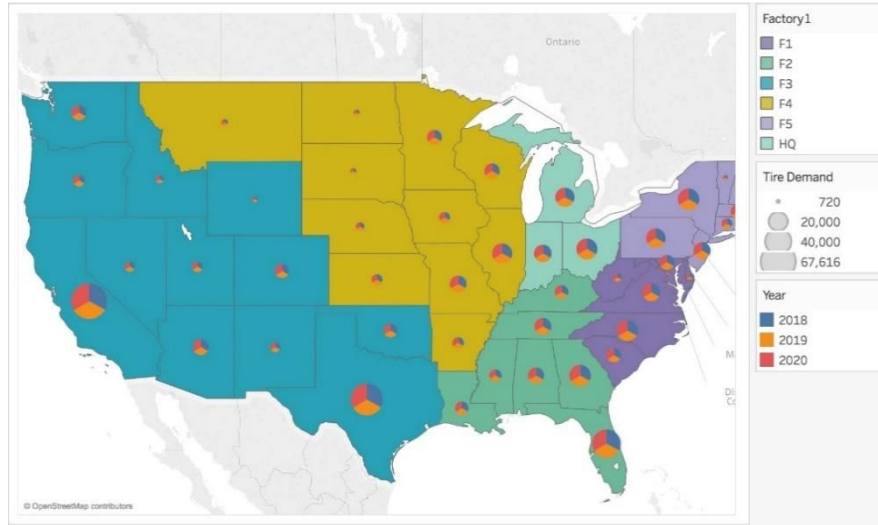


Figure 14: Tire replacement Demand by states and Allocation of Goodyear's Factories

3.4.3 Sensitivity Analysis of PPI-Tire and Tire Demand Growth

According to our model forecast, VMT and PPI-tire are moderately stable in the next 3 years. As a result, tire replacement demand doesn't change much. Until 2020, tire replacement demand is expected to grow by 2.1% in comparison with that in 2017 (less than 1% per year). However, since PPI-Tire closely reflects the market price of raw materials such as rubber and cord which might be highly volatile, we are motivated to measure how a fluctuation in PPI-tire affects the tire demand growth, leaving forecasted VMT constant. As shown in Table 1, a 2.5% growth rate of Tire Replacement in 2020 results from a PPI-Tire of 138.25, decreasing by 7.24 points compared with the baseline. On the other hand, a 1.7% growth rate of Tire Replacement in 2020 need a PPI-tire of 154.77, increasing by 9.28 points.

We can see that a small change in Tire Demand Growth requires a large fluctuation of PPI-tire. Observing the recent variation of PPI-tire, this seems to be unlikely to happen in the next 3 years unless the economy experiences a downturn.

Table 1: Sensitivity analysis of PPI-tire and Tire Demand Growth



Expected Tire Demand Growth (Until 2020)	Impact on Goodyear Sales (units and \$)	PPI-Tire (2020)
2.1%	Base Line	145.49
1.7%	- 0.108M (-\$12.96M)	154.77
2.5%	+0.108M (\$12.96M)	138.25

4. Conclusion & Recommendation

Goodyear has been facing high inventory levels over the past few years, and it is mainly due to the over-forecasting of future tire replacement demand for the passenger vehicle sector. As the Operation Analyst Team, we addressed the problem by using the ARIMA model, which is proven to achieve a more accurate result than the current method, and we suggest Goodyear Executives use this model to project demand from now on. Under this model, the total U.S. vehicle miles traveled from 2018 to 2020 will be 9,888 trillion miles, and the total passenger tire replacement market for the next 3 years is forecasted to be 632 million units. With Goodyear's 13 percent share of the passenger tire replacement market, its estimated total production will be 82.16 million units. Goodyear should prepare resources to produce 27.1 million, 27.4 million, and 27.6 million tire units from 2018 to 2020 respectively. In regards of the regional difference, the big three states---California, Texas and Florida, with demand of 10.71%, 8.55% and 6.79% respectively, maintain their leading role and contribute most of the total national demand.

Currently, Goodyear produce tires for passenger vehicle in six factories in the U.S., including Headquarters in Akron – OH (HQ), Factory in Danville – VA, Gadsden – AL, Lawton – OK, Topeka – KS and Tonawanda – NY. To efficiently serve the market demand as well as reduce delivery cost from factories to distribution centers in different states, Goodyear should allocate its production across the factories based on the shortest distance from the distribution centers to the factories. Specifically, Goodyear



should allocate among Headquarters and its other factories a production volume of 2.57, 2.98, 5.33, 8.6, 3.9 and 3.75 million units respectively in its six factories for passenger vehicle.

Apart from the numeric forecast results, we also recommend the following actions:

1. VMT is expected to stably increase while PPI-tire varies more sharply. This requires Goodyear to work closely with raw material suppliers to predict input prices, PPI and hence tire replacement demand. Throughout the next three years, we don't expect a large variation in tire demand growth (2.1% as expected). However, an economic recession might happen and largely impact PPI and tire demand.
2. Improve model accuracy with the latest updated data. We base our analysis on the assumption that each state contributes to total VMT as well as national tire demand at a constant proportion over the next several years. However, according to the historical graph, VMT experiences different growth acceleration across the time because it is greatly affected by both demographic and economic factors which are sometimes unpredictable or incorrectly forecasted. States with high levels of economic development will possess a faster increase in VMT than others. Therefore, tire demand might be changing differently across the states. Future improvements include a study of dynamics in state contribution to the total tire demand over the years. Another possible improvement includes more studies on how raw material cost and operation expenses in the tire industry such as rubber affect PPI. This would enable Goodyear to establish a more concrete plan for controlling its production costs to achieve higher growth in overall tire demand.
3. Although the tire replacement market has been staggering for years, the rise in autonomous driving, electric cars and ride-sharing is expected to play a larger role in influencing the market's future. It may result in VMT fluctuations over the next few years as these technologies continue to become established. Goodyear should pay close attention to these market developments and adjust its strategy accordingly and effectively to meet future demand.



Appendices

The following Appendices shows the Tables and Figures that support our argument and assist readers to understand the calculation and forecasting. It contains the following 4 sections: **Appendix A** presents data characteristics of our source material; **Appendix B** presents the Winters' Method; **Appendix C** compares the error measurement between Models to validate our selection; **Appendix D** presents the diagnosis results of ARIMA Model; **Appendix E** presents the analysis of the forecast process and results.

Appendix A: Data Characteristics

Table A-1: Descriptive Statistic of U.S. Vehicle Miles Traveled (in millions) from 1970 to 2000 vs. 2001-2017

Year 1970-2000		Year 2001-2017	
Mean	155618.0699	Mean	249276.3873
Standard Deviation ¹⁰	42329.0503	Standard Deviation	17389.36931
Minimum	77442	Minimum	200876
Maximum	247832	Maximum	287358

Table A-2: VMT Seasonal Index from 1970 to 2017

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Seasonal Index	0.902	0.856	1.000	1.001	1.056	1.052	1.088	1.091	1.003	1.031	0.959	0.961

Table A-3: Correlation of Replacement Tire (RT) vs VMT & PPI-Tire

Statistic Index	RT vs. VMT	RT vs. PPI-Tire
Pearson correlation ¹¹	0.979	0.69
P-value ¹²	0.000	0.000

Appendix B: Winters' Method & ARIMA Model

1. Winters's Method

¹⁰ The standard deviation is simply the positive square root of the variance, which is used to measure variability of the data. (Keller, 2018, page 96-100)

¹¹ A positive and negative number indicates a positive and negative relationship between the variables respectively. The larger the absolute value of the coefficient, the stronger the relationship between the variables.

¹² P-value determines whether the correlation between variables is significant. If p-value is less than or equal to the significant level (usually 0.05), the correlation is different from 0. If p-value is greater than the significant level, then you cannot conclude that the correlation is different from 0.



$$\hat{y}_t = (L_{t-1} + T_{t-1}) S_{t-p},$$

where L as level, T as trend, S as seasonality.

$$L_t = \alpha (Y_t / S_{t-p}) + (1 - \alpha) [L_{t-1} + T_{t-1}]$$

$$T_t = \gamma [L_t - L_{t-1}] + (1 - \gamma) T_{t-1}$$

$$S_t = \delta (Y_t / L_t) + (1 - \delta) S_{t-p}$$

L_t : level at time t , α is the weight for the level

T_t : trend at time t ,

γ : weight for the trend

S_t : seasonal component at time t

δ : Index for the seasonal component

p : seasonal period

Y_t : data value at time t

\hat{y}_t : fitted value, or one-period-ahead forecast, at time t

Finally, we come up with the best constants combination as **0.3, 0.1, 0.4**.

2. Multiplicative Seasonal ARIMA Model

$$ARIMA(p,d,q) \times (P,D,Q)_S \quad [Equation 6]$$

In the above mentioned model structure of seasonal ARIMA, the (p,d,q) part is called autoregression (AR); the (P,D,Q) is called moving average (MA); and 'I' refers to integrated. The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged, or prior time period, values. The MA part indicates that the regression error is a linear combination of error terms whose values occurred contemporaneously and at various times in the past. The I, which stands for "integrated", indicates that the data values have been replaced with the difference between their values and the previous. The purpose of each of these features is to make the model fit the data as well as possible.

Non-seasonal ARIMA models are generally denoted $ARIMA(p,d,q)$ where parameters p , d , and q are non-negative integers, p is the number of time lags of the autoregressive



model, d is the number of times the data have had past values subtracted, and q is the order of the moving-average model. Seasonal ARIMA models are usually denoted $ARIMA(p,d,q)(P,D,Q)_m$, where m refers to the number of periods in each season, and the uppercase P,D,Q refer to the autoregressive, differencing, and moving average terms for the seasonal part of the ARIMA model.

Appendix C: Error Measurement

The Table C-1 lists the result of error measurement of Winters' Method and ARIMA Model, where MAPE indication of the error scatter (DeLurgio 1998, page 56), MAD prerepresents amount of dispersion from the mean among the data points (DeLurgio 1998, page 48), and MSE indicates "model's goodness of fit" (DeLurgio 1998, page 54).

Table C-1: Error measurement of Winters' Method and ARIMA Model

Model	Winters' Method			ARIMA Model		
Index	Full	Fitted	Internal	Full	Fitted	Internal
MAPE	0.1160	0.1173	0.1413	0.0920	0.0928	0.0558
MAD	0.0060	0.0061	0.0076	0.00482	0.00487	0.00302
MSD	0.00006	0.00006	0.00006	0.00004	0.00004	0.00002

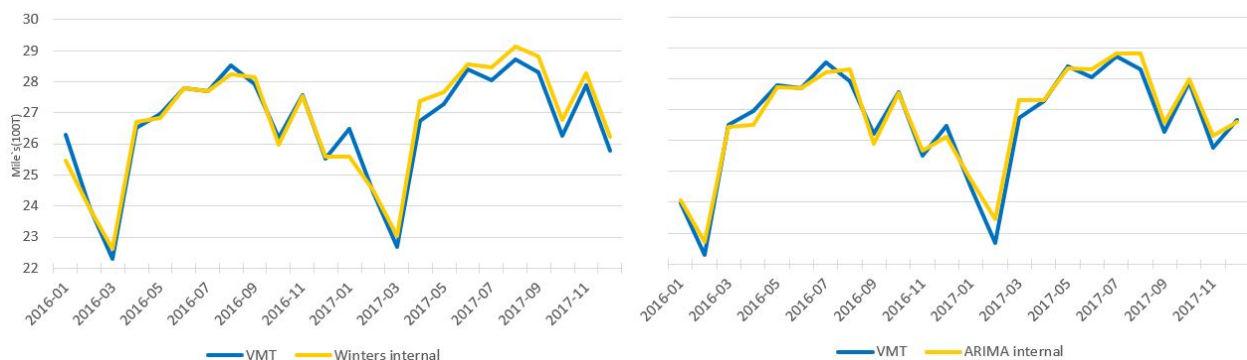


Figure 15: Internal forecast comparison of Winters and seasonal ARIMA (2016~2017)

Appendix D: Model Diagnosis



We summarize the result of the model diagnosis into Table D-1 below. We validate that the residuals, i.e. the difference between the observed values and forecasted data, meet the following assumptions:

1. **Normal:** The normal distribution is described by two parameters, the mean and the standard deviation, and the curve of the data is symmetric about its mean. (Keller 2017, page 251)
2. **Stationary:** Data exhibits constant variances with all observations (Chih-Ling Tsai, 2018, page 5)
3. **Independent:** Data does not have a relationship between observations (Chih-Ling Tsai, 2018, page 5)

Table D-1: ARIMA model diagnosis

Assumption	Test Method	Statistic Result	Decision
Normal	Kolmogorov-Smirnov	p-value<0.01	Pass
Stationary & Independent	Runs Test	p-value=0.623	Pass
	Signs Test	p-value=0.800	Pass
Independent	Autocorrelation Function	N/A	Pass

Interpretation of these results:

- **Normality:** Due to several extreme values such as Feb,1970, the p-value is less than the significance level¹³ 0.05. However, we also look at other informal test such as histogram, the residuals should be regarded as normally distributed.
- **Stationary:** both p-value for Runs test and Signs test are greater than significance level 0.05, so the residuals are stationary.
- **Independence:** The Autocorrelation Function for Residual graph in our test shows a weak spike at lag 23 and lag49, indicating that there is still some mild autoregressive term in the ARIMA model. In general, the residuals are independent, except some

¹³ The significance level α is the probability of making the wrong decision when the null hypothesis is true. Alpha levels (sometimes just called “significance levels”) are used in hypothesis tests. Usually, these tests are run with an alpha level of .05 (5%). Statistics How To, <http://www.statisticshowto.com/what-is-an-alpha-level/>



other unexplainable factors affecting the results.

Appendix E: Forecast the Tire Replacement, PPI-Tire, and Goodyear Tire Replacement (Passenger) Market Share

1. Tire Replacement Forecast Regression Model

As introduced in section *Data Characteristics*, we assume that the dependent variable - tire replacement, is strongly related to the mileage people traveled and is sensitive to Producer Price Index. Such relationship can be expected to be represented by the following equation:

$$\text{Tire Replacement} = \beta_0 + \beta_1 \text{VMT} + \beta_2 \text{PPI} + \varepsilon \quad [\text{Equation 3}]$$

where β_0 is the intercept; β_1 and β_2 are the coefficients of the independent variables; ε is error variable.¹⁴

Table E-1: Tire Replacement Regression Output

Adjusted R Square ¹⁵	0.962722	Index	Coefficients	P-value
		Intercept	117.566663	5.85459E-06
		VMT	5.05424E-05	9.25802E-25
		Log PPI-Tire	-33.98132859	0.013058043

2. Forecast PPI-Tire

We use Winters' Method with a constant combination of (0.9, 0.1, 0.3) to forecast PPI-Tire for next 3 years, and the results is illustrated as follows:

Table E-2 Production Price Index - Tire from 2018 to 2020 in varying scenarios

Year	Conservative	Expected	Aggressive
2018	139.50	145.33	151.15
2019	129.74	145.41	161.08
2020	119.82	145.49	171.16

¹⁴ Error variable: there are four required conditions for error variable ε : 1.the probability distribution of the ε is normal; 2.the mean of ε is zero. 3. The standard deviation of ε is σ_ε , which is a constant; 4. The ε is independent. [Keller 2017, page 695]

¹⁵ Adjusted R2 give you an idea of how many data points fall within the line of the regression equation.



3. Forecast U.S. Tire Replacement and Goodyear Market Volume

Given the forecasted VMT, PPI-Tire and Goodyear's current market share of 13%, we can use the Equation 4 to estimate the U.S. Tire Replacement demand, and predict Goodyear Tire Replacement market volume as well.

Table E-3: U.S. Tire Replacement (in millions) Forecast from 2018 to 2020 in varying scenarios

Year	Conservative	Expected	Aggressive
2018	201.8	208.6	215.7
2019	200.3	210.7	221.7
2020	199.4	212.7	227.3
Total	601.5	632.0	664.7

Table E-4: Goodyear Tire Replacement (in millions) Forecast from 2018 to 2020 in Varying Scenarios

Year	Conservative	Expected	Aggressive
2018	26.23	27.10	28.05
2019	26.04	27.35	28.82
2020	25.92	27.60	29.55
Total	78.91	82.05	86.42

Map E-5 & Table E-5: Goodyear Facility Address and Geocode



Facility	Address	Latitude	Longitude
HQ	200 Innovation Way, Akron, OH	41.1	-81.5
F1	1901 Goodyear Blvd, Danville, VA	36.5	-79.4
F2	922 E Meighan Blvd, Gadsden, AL	34.0	-86.0
F3	1 SW Goodyear Blvd, Lawton, OK	34.6	-98.5
F4	2000 US-24, Topeka, KS	39.1	-95.7
F5	10 Sheridan Dr, Tonawanda, NY	43.0	-78.9

Table E-6: Goodyear Tire Replacement (in thousands) by States forecast (2018-2020)

State	Factory	Tire Demand 2018	Tire Demand 2019	Tire Demand 2020	State	Factory	Tire Demand 2018	Tire Demand 2019	Tire Demand 2020
Alabama	F2	591	597	603	Missouri	F4	632	638	644
Alaska	F3	45	47	47	Montana	F4	108	110	111
Arizona	F3	562	567	573	Nebraska	F4	177	178	180
Arkansas	F4	305	309	313	Nevada	F3	229	230	232
California	F3	2,906	2,933	2,962	New Hampshire	F5	115	118	119
Colorado	F3	446	449	454	New Jersey	F5	659	665	672
Connecticut	F5	270	274	277	New Mexico	F3	238	241	243
Delaware	F1	87	88	89	New York	F5	1,050	1,060	1,070
District of Columbia	F1	31	30	30	North Carolina	F1	997	1,008	1,018
Florida	F2	1,841	1,860	1,878	North Dakota	F4	83	85	86
Georgia	F2	1,049	1,060	1,070	Ohio	HQ	1,013	1,024	1,034
Hawaii	F3	91	93	94	Oklahoma	F3	419	422	426
Idaho	F3	147	148	149	Oregon	F3	314	318	321
Illinois	F4	917	926	935	Pennsylvania	F5	866	874	882
Indiana	HQ	711	718	725	Rhode Island	F5	68	68	69
Iowa	F4	285	288	290	South Carolina	F1	466	471	476
Kansas	F4	274	277	279	South Dakota	F4	81	82	83
Kentucky	F2	421	424	429	Tennessee	F2	657	663	669
Louisiana	F2	420	424	429	Texas	F3	2,317	2,342	2,365
Maine	F5	127	129	130	Utah	F3	269	271	274
Maryland	F1	505	509	514	Vermont	F5	63	63	64
Massachusetts	F5	528	534	539	Virginia	F1	722	728	736
Michigan	HQ	849	857	866	Washington	F3	521	526	531
Minnesota	F4	504	509	514	West Virginia	F1	167	170	171
Mississippi	F2	348	351	354	Wisconsin	F4	547	553	559
					Wyoming	F3	80	79	80

Table E-7: Goodyear Tire Production for Passenger Vehicles by Factories (in thousands)
Forecast from 2018 to 2020



	2018	2019	2020
HQ	2,573	2,599	2,625
F1	2,975	3,004	3,034
F2	5,328	5,379	5,432
F3	8,582	8,665	8,751
F4	3,914	3,955	3,994
F5	3,746	3,785	3,822



Reference

- i. DeLurgio, S. A. (1998). Forecasting Principles and Applications. In S. A. DeLurgio, *Forecasting Principles and Applications*. Irwin McGraw Hill.
- ii. Tsai, C.-L. (2018). *MGT 203B Notes - Forecasting and Managerial Research Methods*. UC Davis Graduate School of Management.
- iii. Tsai, C.-L. (2018). *MGT 285.- Time Series Analysis and Forecasting*. UC Davis Graduate School of Management.