Engineering and Management

Management of Sustainability and Technology

Master Thesis

The Impact of Supplier Lead Time on the Automotive Supply Chain

Supervisor:
Dr. Mangano Giulio

Candidate:
Oggero Anna

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Abstract

This thesis aims to investigate the influence of suppliers' lead time on the automotive supply chain through a linear regression-based analysis. The primary objective is to explore the correlation between lead time and pertinent variables such as distance from suppliers, category of goods supplied, unit cost, quantities received, and discrepancies in deliveries. By employing statistical techniques, the study has the objective to comprehend how these variables interact with each other, with a specific focus on how lead time impacts supply chain processes. The research centers on interpreting the correlations derived from the collected data, seeking to provide a comprehensive understanding of the dynamics governing the relationships between suppliers and manufacturers in the automotive sector. The results obtained will establish an analytical foundation for a more profound comprehension of the impact of delivery times on supply chain management.

1. The Automotive Supply Chain: Introduction

The automotive supply chain is a highly complex and intricate system, involving a large number of suppliers ranging from those producing small parts to major components like engines. In recent years the automotive sector, like many other global industries, has undergone significant changes, determined by factors such as the globalization of production, the advancement of innovative technologies, and a growing emphasis on environmental thematics.

One of the main changes in the automotive supply chain is its evolving structure. Over the years, the system has become more integrated, partly due to the adoption of innovative techniques such as Just-In-Time (JIT) and Lean Manufacturing, the adoption of these strategies reduces costs and production times and improve quality. (Piątek, 2023, Bhamu & Singh Sangwan, 2014). Just in Time (JIT) is a production strategy that is based on minimizing waste, producing goods only at the exact moment when they are required, thus reducing inventory and associated costs. Lean manufacturing, on the other hand, is a systematic approach to improve the overall efficiency of business processes, eliminating waste and optimizing the use of resources to maximize value for the customer. The JIT theory, pioneered by Toyota, has demonstrated how minimizing idle time and waiting periods can lead to a more efficient system, increasing production efficiency and reducing inventory costs (Ohno, 1988).

The documented trend towards increasing globalization is also evident, which has allowed a repositioning in the sphere of international automobile production through the search of better quality-price goods. This has resulted in a more complex supply chain, making it challenging to manage communication between system actors and logistical flows.

Finally, it is also important to consider the impact of environmental issues on the automotive supply chain. Emissions regulations and the shift to electric vehicles have increased demand for sustainable materials such as lithium for batteries, while reducing that of traditional engine components. The circular economy is driving the reuse and recycling of materials, changing production processes. Logistics is becoming more digital to optimize transport and reduce energy consumption. In addition, there is a growing need for traceability to ensure the use of resources from sustainable sources. In short, the supply chain is becoming more sustainable and efficient.

In conclusion, the automotive supply chain is constantly evolving and influenced by various factors, including changes in the global economy, technological advancements, and the increasing importance of environmental considerations. It's crucial for all producers and suppliers to invest and adapt to these changes to maintain competitiveness in a sector that becomes more challenging each year.

The production chain in the automotive sector is more complex and morphological than ever before. Its structure consists of levels, stages, methods and models.

1.2 The Levels of the Supply Chain in the Automotive Industry

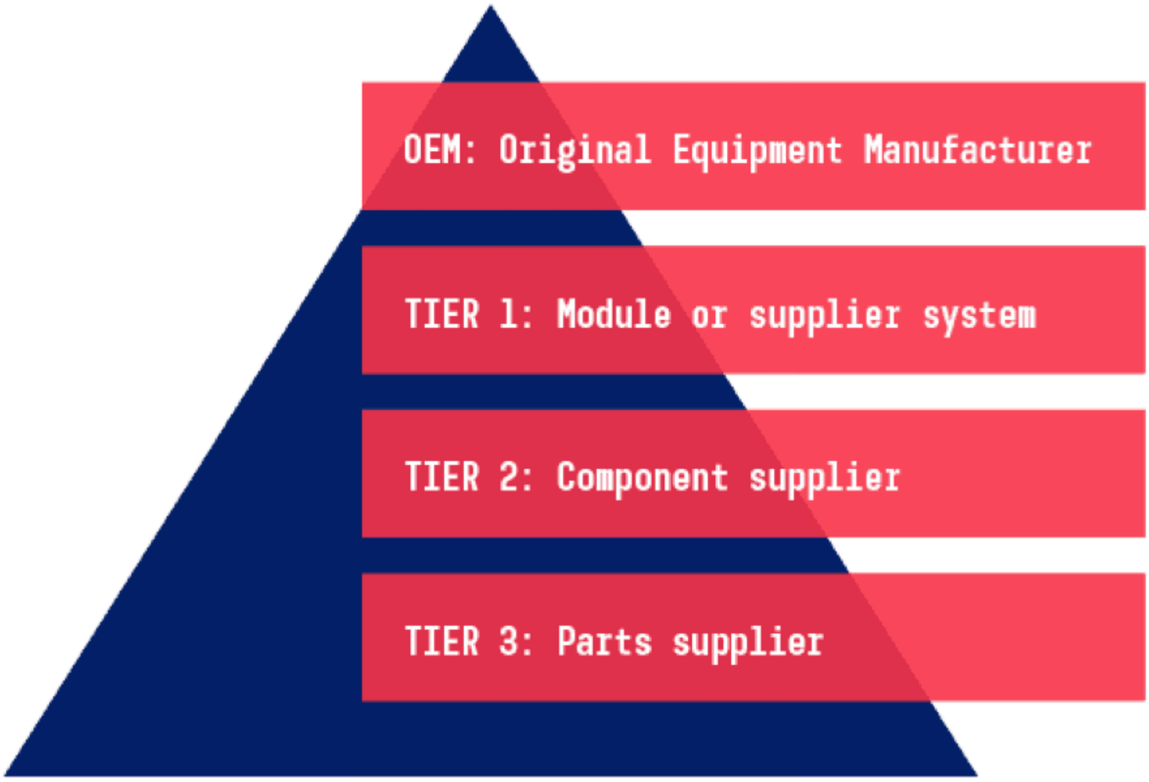

Figure 1: Tiers of the automotive supply chain - https://ecosio.com/en/blog/what-is-a-tier-supplier/

The automotive supply chain comprises three main tiers and is a complex system that requires optimal management for perfect coordination of all the flows to maintain global competitiveness (Chopra & Meindl, 2016; Rotjanakorn, Sadangharn, & Na-Nan, 2020) and consists of three main levels.

- The first-tier suppliers collaborate directly with the Original Equipment Manufacturer (OEM) by supplying complex components and integrating systems. The partnership between the OEM and first-tier suppliers is crucial for rapid responses to market changes, developing new technologies, and achieving maximum production efficiency.

- Second-tier suppliers work with first-tier suppliers, providing materials and components. Although less visible, they significantly impact the quality and cost of final components of first-tier suppliers and influence production punctuality and precision (Chopra & Meindl, 2016).
- Third-tier suppliers provide basic components, this is the most critical level, as any lack or delay in the supply can lead to a complete interruption of the supply chain.

1.3 Stages of the Automotive Supply Chain

The automotive supply chain consists of different stages, each with a specific role. The interaction and coordination between these stages are crucial for achieving efficiency and punctuality in the production of the final product.

Five stages can be highlighted, described below.

Stage 1: Supply of Raw Materials

Raw materials are the basic components that are prone to fluctuations in prices and availability, which can cause significant problems throughout the supply chain. The procurement process for raw materials is vital as they form the foundation of the supply chain, and any potential shortage of these products can halt the entire production process.

Stage 2: Component Manufacturing

Raw materials are transformed into automotive components such as engines, electronic systems, and bodywork. This stage requires collaboration across all three tiers of the supply chain, with each producing specific parts that contribute to the final product. Using high-quality products is crucial in ensuring vehicle safety and reliability, and in reducing defects and production costs. Effective collaboration and communication between suppliers and manufacturers are essential for achieving this goal (Dyer & Hatch, 2006).

Stage 3: Vehicle Assembly

Components are assembled to create the final product. Over the years, the implementation of innovative technologies and techniques such as Lean Manufacturing has increased efficiency, resulting in reduced time and costs, as well as improved product quality. Lean

Manufacturing helps minimize losses and enables dynamic responsiveness to changes in market demand.

Stage 4: Distribution and Logistics

This stage is complex, involving global logistics management and various means of transportation, including trucks, trains, ships, and aircraft. Precise coordination is necessary to minimize costs and reduce delays. Logistic management is challenging as it must balance costs, punctuality in deliveries, and increasing attention to environmental sustainability (Chopra & Meindl, 2016).

Stage 5: After-Sales Services

After-sales services, such as maintenance, repairs, and spare parts supply, are essential for customer satisfaction and brand loyalty. This process can enhance brand perception and customer loyalty, making it a key element for the long-term success of car manufacturers.

1.4 Main methods of inventory and production management within the supply chain

In today's competitive business environment, companies need to continually adjust their production and inventory management strategies to effectively address market challenges. Some of the main techniques for optimizing resources, minimizing costs, and meeting customer expectations are: Just-In-Time (JIT), Just-In-Case (JIC), Build-to-Stock (BTS), and Build-to-Order (BTO).

1. Just-In-Time (JIT): This strategy aims to minimize inventory by ensuring that components and materials arrive at the assembly line just when needed. This reduces inventory costs and optimizes production flow (Ohno, 1988, Mackelprang & Nair, 2010, Jiang, Rigobon, & Rigobon, 2021) and often the adoption of this methodology is associated with an increase in the company's performance. However, the use of this technique can increase production costs and make it more difficult to manage the production.

2. Just-In-Case (JIC): Unlike JIT, this strategy maximizes inventory to accommodate unforeseen fluctuations in demand and maintain production continuity (Monden, 2011, Herold & Marzantowicz, 2023, Jiang, Rigobon, & Rigobon, 2021). Disadvantages include

high inventory and stock management costs, risks of merchandise obsolescence, and greater capital investment for safety stocks.

3. Build-to-Order (BTO): products are assembled after an order is received, reducing the risk of unsold inventory and allowing for greater flexibility and customization, offering a competitive advantage in markets characterized by high variability of demand (Villar, Paladini, & Buckley, 2023). Flexibility is influenced by factors such as integration of information and production flexibility. (Reichhart & Holweg, 2007). However, this method may lead to higher production costs and increased production management complexity.

4. Build-to-Stock (BTS): This strategy relies on demand forecasts and safety stock creation to ensure continuous production. While it allows for prompt response to customer requests, it can result in overstock and associated costs, reducing supply chain flexibility. (Katsaliaki, Galetsi, & Kumar, 2022).

These methodologies can be categorized into push and pull approaches, with the first two mainly focused on inventory management and the last two on production management. Push and pull systems are the two most widely used production methods and have a direct impact on inventory management and production

- Pull approach: Production and inventory are guided by demand, based on low inventory levels and rapid response to market changes to reduce waste. It reduces waste and operating costs, improving supply chain efficiency compared to the push model. (Yang, Cai, & Chen, 2018). This includes JIT for inventory management and BTO for production management.

- Push approach: Production and inventory are based on long-term planning, employing JIC for inventory management and BTO for production management. (Yang, Cai, & Chen, 2018).

1.5 The Globalization of the Supply Chain in the Automotive Sector

The automotive industry is a pillar of the global economy with significant impacts on GDP, employment and supply chain. Its role is not limited to vehicle production but extends to a wide network of sectors and related activities.

The globalization of the supply chain is a crucial aspect in the automotive industry because it has significantly transformed production and logistics processes. The modern supply chain now spans across all continents and involves suppliers from around the world, aiming to optimize costs, quality, and production times. Car manufacturers must adapt to this global trend in order to remain competitive in the market.

Globalization provides access to specialized resources worldwide, enabling cost reduction and improved operational flexibility. According to Christopher and Holweg (2011), the globalization of supply chains allowed automotive companies to leverage economies of scale, optimize global production, and improve operational efficiency. (Christopher & Holweg, 2011). However, this process also introduces high organizational complexity, as coordination is required with suppliers from various parts of the world while respecting quality standards and regulations of different countries.

The entire supply chain has been affected by this phenomenon.

- **Impact on levels**

  Tier 1 suppliers, who work directly with the OEM to supply key components, have expanded their network globally, increasing the complexity of the supply chain. Tier 2 suppliers, who provide sub-components, have had to deal with growing global competition, leading to cost reductions and price fluctuations (Ivanov, Dolgui, & Sokolov, 2019). Finally, tier 3 suppliers, who supply raw materials, have faced similar challenges as tier 2 suppliers. The global expansion of the supply chain has increased competitiveness and presented more challenges in reducing costs and addressing environmental sustainability (Herold & Marzantowicz, 2023).

- **Impact on stages**

  Globalization has impacted all stages of the automotive supply chain. Companies are sourcing raw materials from countries like China and Russia to reduce costs, introducing risks such as price fluctuations and geopolitical challenges (Ivanov, Dolgui, & Sokolov, 2019). Production of components has been shifted to regions with low-cost and high-productivity labor forces, such as Southeast Asia and Eastern Europe. Vehicle assembly has expanded in emerging markets to reduce costs and be closer to customers, complicating global-level logistics management. Car manufacturers must now address challenges such as tariffs, trade restrictions, and transit times, which influence the speed and efficiency of the transport network (Christopher & Peck, 2004, Katsaliaki, Galetsi, & Kumar, 2022).

- **Impact on methods**

As a consequence of the diffusion of this phenomenon, practices such as Just In Time (JIT) and Build to Order (BTO) have become fundamental. The increasing global complexity has induced some car manufacturers to adopt the JIT logic in order to improve the efficiency and reduce inventory costs (Holweg, 2007). To cope with the increasing variability of the global markets, the BTO has been integrated. This method allows companies to better respond to the rapid changes of the global market and to better adapt to the specific requests of the customers.

- **Italian market**

The Italian automotive sector is facing a particularly critical situation. The combination of global and local factors has led to a context of unprecedented challenges for the entire supply chain. The growing pressure for an ecological transition, with increasingly stringent EU emission standards and the imminent stop to sales of cars with internal combustion engines, has put many traditional manufacturers in a crisis. Moreover, the adoption of electrification has been slower than in other countries, making it difficult for Italy to maintain its competitiveness on the international market. In this context Stellantis, the result of the merger between Fiat Chrysler and the PSA group, plays a crucial role. This company has put in place a strategy to accelerate the transition towards electrification, investing in new platforms for electric vehicles and in battery production, with the aim of maintaining a strong competitive position. However, despite these efforts, Stellantis is also facing considerable difficulties in balancing the global demand for electric cars with delays in the conversion of Italian factories. They need rapid modernization to avoid loss of competitiveness with international competitors. The commodity crisis, further aggravated by global geopolitical tensions, has increased production costs. Italy's dependence on imports of components and materials, particularly from countries such as China and India, has made the sector vulnerable to disruptions in supply chains. This has led to a rise in prices, making it even more difficult for Italian companies to compete on the global market, especially with automotive giants who have more resources to face these challenges. The sector is also facing declining domestic demand. Economic uncertainty and rising cost of living have reduced the purchasing capacity of Italian households, which is reflected in a stagnant car market. Although exports continue to be a major part of the sector, the slowdown in global demand due to recession in some key economies has reduced opportunities for growth abroad. This is compounded by fierce competition from electric vehicle (EV) manufacturers, particularly Chinese ones, who are invading European markets with cheaper and technologically advanced models. Italian car manufacturers, despite their fame for design and performance, are struggling to keep up in an industry that is rapidly transforming itself towards electric and sustainable mobility.

Globalization has deeply transformed the automotive supply chain, adding new challenges and opportunities. On one hand, it has allowed access to specified resources all over the world, reducing operational costs and increasing efficiency. On the other side, globalization has increased organizational complexity, further complicating the supply chain and introducing higher quality standards. (Sakuramoto, Di Serio, & Bittar, 2019, Kano, Tsang, & Yeung, 2020).

Companies have had to face new challenges in terms of price fluctuations, geopolitical risks, and a crescent attention to the environmental aspect. All these factors have pushed many manufacturers to expand their market at a global level, increasing the difficulty of the logistic fluxes management.

In conclusion, globalization has introduced many advantages but at the same time many challenges, just companies who will be able to adapt to these new dynamics will maintain and increase their competitiveness within the global market.

1.6 The importance of Lead Time in the Automotive Supply Chain

With the rise of globalization, managing the supply chain has become increasingly complex. A potential delay in delivery from a third-tier supplier can lead to a domino effect of slowdowns throughout the entire production chain. Furthermore, automotive companies need to quickly adapt to any disruptions and changes in customer demand. The lead time is the time between the placement of an order and the delivery of the product or component to the final company. This factor is crucial in supply chain management, particularly in the automotive sector, where precision and timing are essential. Lengthy lead times can disrupt production, leading to delays in delivering products to customers and impacting the company's reputation.

Many companies adopt the principal strategy of Just In Time, focusing on maintaining the lowest possible level of stocks. In these cases, reducing lead times is crucial to reduce inventory costs and improve production efficiency. Techniques such as Just In Time and Lean Manufacturing aim to eliminate waste, reduce downtime, and optimize production flows. In this context, a short lead time is very helpful because it allows us to minimize inventory levels and receive components just in time to start production. This also reduces the risk of a drop in customer demand, which could lead to product obsolescence and high inventory costs. In a sector like the automotive industry, it is crucial for companies to be able to rapidly respond to changes in market demand.

In summary, effective lead time management is crucial for ensuring a company's efficiency, timeliness, and responsiveness in a highly competitive market.

1.7 Conclusion

In conclusion, the literature reviewed shows that the automotive supply chain is a highly complex and constantly evolving system, influenced by multiple factors such as globalization, The adoption of new technologies and increasing attention to the environment. Production management strategies, such as Just-In-Time (JIT) and Build-to-Order (BTO), play a key role in improving efficiency and reducing operating costs. However, these techniques require careful management of delivery time and high flexibility to adapt to market changes.

Globalization has radically transformed the structure of the supply chain, increasing competition but also management complexity, with a greater need for coordination between global and local suppliers. The Italian automotive sector, for example, has had to face these challenges, maintaining competitiveness through growing exports and a strong integration of foreign components.

In summary, the ability of car manufacturers to adapt to global dynamics and new technologies will be crucial for maintaining their competitiveness. Efficient supply chain management and prompt response to market disruptions or changes are key elements for success in an increasingly competitive industry.

2. The Linear Regression and ANOVA: Theoretical Foundations and Applications

Linear regression and ANOVA (Analysis of Variance) are among the most common statistical tools employed to analyze and interpret data. Both these methodologies help to understand the relationships between one or more variables and study how certain ones, defined as independent, influence another, called dependent.
Although they differ slightly in purpose, the theoretical basis of these statistical tools is common and focuses on analysis of variance.

Linear regression is a statistical technique that studies the relationship between a dependent variable and one or more independent variables, which usually are continuous values. This model is described by the equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

Where Y is the dependent variable, X_1, X_2, …, X_n are the independent variables, β_0 is the intercept, β_1, β_2, …, β_n are the regression coefficients, and ε represents the residual error.
Linear regression allows for quantifying the influence of independent variables on the dependent variable, facilitating data prediction and analysis.

The regression coefficients β_1, β_2, …, β_n represent the marginal effect of each independent variable on the dependent variable. This means that if the independent variable increases by one-unit the dependent variable will vary by an average value equal to the value of the coefficient, if all the other variables are held constant.

The fundamental assumptions that must be satisfied to ensure the validity of results are the following:

- Linearity: This condition must be verified for what regards the relation between the independent and dependent variables.
- Independence: The errors must be independent between each other.
- Homoscedasticity: All the independent variables must have a constant variance of the error.

- Normality of errors: The errors must follow a normal distribution, and this condition can be verified by the analysis of the Residual Plots graphs.

In particular, when analyzing the last point, it is possible to provide a more detailed description. Generally, the residual plot graphs consist of the normal probability plot, the Histogram, the residual vs. order and the residual vs. fit graphs. In the first scenario, for a normal distribution, the points should align along a straight line. In the second case, they should be distributed in a bell-shaped pattern. Finally, in the last two graphs, the points should be randomly distributed around zero without displaying any specific pattern.

To assess the adequacy of a linear regression model, various metrics are used, the most important are the following.
The coefficient of determination (R^2) which is an index that measures the link between the variability of the data and the correctness of the statistical model used. A value of R^2 close to 1 indicates that the model fits the data well.
The p-value instead is used to test the hypothesis that a regression coefficient is equal to zero and measure the statistical significance of a variable. If its value is less than 0.05 the coefficient is statistically significant.
Another value that is presented in the analysis is the t-value, which is an indicator of the difference between the means of the different variables. A high t-value indicates a greater difference between the means of the indicators.
Often, these two terms are analyzed together. A low p-value associated with a high t-value indicates a strong statistical significance of the variables.
Finally, it is important to consider the variance inflation factor (VIF) that quantifies the severity of multicollinearity. This phenomenon occurs when two or more independent variables in the model are highly correlated and can lead to unstable regression coefficients and misleading interpretations. If the VIF value is greater than 5 (or, in some cases, greater than 10) it is possible to have an issue of multicollinearity.

If this problem emerges, three principal strategies can be carried out:

- Removal of collinear variables: eliminate the independent variables with the highest VIF value.
- Combining variables: create new variables by combining the ones with present multicollinearity.

- Regularization: penalize regression coefficients which display the issue using regression techniques such as Ridge Regression or Lasso.

Linear regression is a powerful and versatile tool for data analysis. To obtain valid results is important to understand the assumptions, correctly interpreting regression coefficients, and paying attention to multicollinearity. The variance inflation factor (VIF) represents an important diagnostic tool for identifying and managing this issue, ensuring that regression models are robust and interpretable.

Another tool used to analyze data correlation is ANOVA (Analysis of Variance).
The main focus of the study is analyzing the relation between the categorical variable and the dependent one and so the interest of the analysis is focused on the differences in group means.

The fundamental concept is to determine whether the observed differences in group means can be explained by a systematic cause or can be attributed to chance. In other words, this tool allows us to understand if the factors under examination have a significant effect on the dependent variables.

There are some key assumptions underlying this method:

- The observations within each group are independent from each other.
- The populations from which the samples come from are normally distributed.
- The populations from which the samples come from have homogeneous variances (i.e., similar variances between groups).

It is important that all these assumptions are verified before the conduction of the analysis, as violating any of them can compromise the results.

The logic is explained through comparing two types of variability: between-groups variability and within-groups variability. Respectively, the former measures how much the group means differ from each other, while the latter measures how much the observations within each group differ from the respective group mean.

There are different models of ANOVA, each suitable for specific situations.

- One-way ANOVA is used when comparing a single independent variable.

- Two-way ANOVA extends this analysis to two independent variables, allowing for the examination of not only the main effects of each variable, but also their interactions.
- Other variants include repeated measures ANOVA, used when the same units are measured under multiple conditions, and multivariate ANOVA (MANOVA), which allows for the analysis of multiple dependent variables simultaneously.

Even though linear regression and ANOVA may have different applications, both have a common point: variance analysis. In linear regression, the total variance of the dependent variable is decomposed into variance explained by the independent variables and residual one. Similarly, ANOVA decomposes the total observed variability in the data into between-groups and within-groups variability. This approach allows for evaluating if the observed differences in group means are statistically significant, helping to assess the effects of examined factors on the dependent variables.

Linear regression is particularly useful for modeling and predicting behaviors or phenomena where the relationship between variables is linear. It is widely used in fields such as economics, biology, psychology, and social sciences, where the aim is to understand how independent variables quantitatively influence the dependent variable.

On the other hand, ANOVA is mainly applied when comparing the means of three or more groups, such as in the study of the effects of different treatments or experimental conditions on a variable of interest. It is essential to verify some fundamental assumptions, including the homogeneity of variances between groups and the normality of the distributions of the populations from which the samples come, to obtain valid and meaningful results.

In conclusion, both linear regression and ANOVA are powerful tools for the statistical analysis of data, each with its own peculiarities and specific applications. Understanding their theoretical foundations and the correct method of application is essential for obtaining reliable and informative results in scientific research and quantitative analysis.

3. Definition of the Mental Model for Data Analysis in the Automotive Supply Chain

3.1 Introduction

In today's automotive industry, managing the supply chain is a crucial challenge. The sector involves a large network of suppliers spread across the globe, each facing specific laws and operational constraints. To stay competitive in the global market, car manufacturers must ensure continuous production, offer a good price-to-quality ratio, quickly adapt to demand fluctuations, and meet every customer's request. To achieve this, certain variables characterize every automotive company and need to be monitored, as their interaction will determine a company's success.

This chapter will analyze some of the most influential variables and explain their importance in the context of supply chain management.

3.2 Automotive Industry Context

In the previous chapter, we discussed how the automotive sector has a complex supply chain with a wide variety of suppliers that need to be perfectly coordinated. This industry is influenced by economic factors, environmental regulations, and technological trends such as the electrification of vehicles. It's important to note that these suppliers are located in different parts of the world and are subject to different laws, making supply chain management even more challenging. Managing these variables effectively is crucial in order to offer the best product in the market and to maintain a strong position within the sector (Christopher, 2016).

3.3 Description of the company

The company under review is distinguished by a highly strategic approach to supply management, based on the use of open orders. An open order is a type of long-term contract between a company and a supplier, in which the general terms of delivery are defined in advance, such as prices, expected quantities and delivery methods, but without specifying the details of each individual shipment. In practice, once the agreement is signed, the company issues periodic purchase orders, usually weekly or monthly, based on its demand planning, without having to renegotiate the terms for each supply. This ensures continuity of supply and allows for more efficient and flexible management of material flows, without having to issue a new specific order every time a particular product needs to be delivered.

The open order system allows the company to maintain stable and continuous relationships with suppliers, selected for their reliability and ability to meet business needs. Once a supplier has been chosen, it is not necessary to intervene frequently to change or update the contract details, which reduces the administrative and operational time involved in managing the procurement. This approach differs from the "just in case" system (where you keep excessive stocks to avoid problems) and allows the company to reduce the costs and risks associated with maintaining high levels of inventory, At the same time, it optimizes the ability to respond to demand.

One of the company's main objectives is to keep stock levels as low as possible, by adopting a just-in-time strategy. This management philosophy is based on the idea of receiving materials only when they are needed for production, thus minimizing inventory costs and reducing the risk of obsolescence or deterioration of materials. In a sector such as the automotive industry, and particularly in the production of luxury vehicles, efficient stock management is essential to maintain the flexibility needed to respond quickly to changes in demand, without compromising quality or production time.

Moreover, the open order system, integrated with the just-in-time strategy, is particularly effective for a company that has as its main customer a world leader in the luxury automotive sector. This customer imposes very high standards in terms of material quality and on-time delivery, making impeccable supply chain management essential. Delivery time adherence is essential to avoid production slowdowns and ensure that luxury vehicles are produced on time without compromising quality. Furthermore, as the luxury industry requires the highest quality materials, maintaining stable and long-lasting relationships with trusted suppliers ensures that each component meets the high standards required.

This analysis was carried out with the main objective of examining the influence of suppliers' lead time on production performance. Lead time, the time between sending an order and receiving the material, is a critical variable for the company, as it directly affects the ability to efficiently plan and manage production. Delays in delivery times can have a significant impact on the production chain, causing delays or interruptions that may lead to additional costs or, in the worst case, problems with the delivery of the final product.

To justify the choice of focusing on the analysis of lead time, a number of additional variables, that will be analyzed later, have been taken into consideration, which have an equally significant impact on supply chain management. These variables include distance from suppliers, category of goods supplied, unit price of goods, quantity received, quantity discrepancy, total cost of the order and time offset.

In conclusion, the company’s approach, which is based on open orders and just-in-time strategy, is effective in managing the complexity of the automotive supply chain. The analysis of lead time and other variables described above provides a clear picture of the importance of optimized supply and logistics management to ensure the punctuality and quality necessary to meet the needs of a luxury customer, Ensuring both operational efficiency and flexibility.

3.4 Analysis of variables

3.4.1 Lead time

The most influential variable after distance is lead time, which is the time between placing an order and receiving it. This factor determines how various aspects of the supply chain are organized, including production planning, inventory management, and the ability to respond to changes in demand (Li et al., 2019).

Another risk faced by a company that interfaces with suppliers characterized by very long lead times is that of having to manage very large batches. This may be linked to the company's choice to order large quantities in order to balance the cost of transportation, or it could be the supplier himself who requests large batches to ship. As a result, the company will have a very large stock of that product which leads to high warehouse costs and at the same time runs the risk that a decrease in demand could cause the product to become obsolete.

3.4.2 Distance of Suppliers from the Company

The geographic distance is one of the most determinant variables in the management of the supply chain. The management of suppliers located far away in the world involves important logistic challenges such as longer transit time, higher transportation costs, and higher risks of delays. These factors directly influence the production process of a company and may cause inconvenience that could damage the company’s image.

Transport costs have a significant impact on the total cost of the supply chain, and it is intuitive to understand that they increase with the distance. Additionally, it is necessary to consider that these costs can be influenced by variations induced by fluctuation of the fuel price, of the customs tariffs, and by geopolitical risks which can threaten the continuity of the production. (Milewska & Milewski, 2022, Gurtu, Jaber, & Searcy, 2015)

Another risk of including in the supply chain suppliers located far away is that they could be more vulnerable to interruptions in the furniture of goods due to natural disaster, political changes or infrastructural problems. Additionally, having a more dislocated supply chain can reduce the ability of the leading company to directly control all the processes, increasing the uncertainty. (Vanany, Zailani, & Pujawan, 2009)

An example is the terrible earthquake and tsunami that hit Japan in 2011 which had a devastating impact on the totality of the automotive supply chain. Producers and suppliers of microchips and other electrical systems, which are mainly located in this world area, have been severely damaged and this caused the interruption of the furniture of these components. This event had global repercussions causing the temporary interruption of the production of many automotive companies. (Arto, Andreoni, & Rueda Cantuche, 2015)

3.4.3 Product Category

The categorization of products is crucial for determining supply strategies, stock management, and logistics. Each category has specific needs that must be considered in supply chain management, such as delivery times, transportation conditions, and storage requirements (Benrqya et al., 2014).

Products can be classified based on their value, volume, weight, and other physical characteristics. For instance, expensive and delicate components like electrical circuits require careful risk control to avoid damages during transport. Moreover, these products often have highly volatile demand, so one option to mitigate risks is to use a make-to-order storage strategy, organizing production according to orders to reduce inventory levels.

On the other hand, bulky and heavy mechanical components like engines pose challenges related to transportation and storage costs.

3.4.4 Unit Price of Goods

The unit price of a product is a fundamental variable to be considered in the supply chain management of an automotive company, but it cannot be evaluated in isolation. Although the globalization of the supply chain often leads companies to look for international suppliers in order to obtain a more competitive price. The unit price analysis must take into account various factors that affect the overall efficiency of the supply chain, including product quality and suppliers' lead time.

In the context of globalization, it is common for companies to choose more distant suppliers to obtain lower unit costs. However, a lower price does not always guarantee a better overall result, as choosing suppliers based solely on cost can lead to compromises in terms of delivery times and material quality.

In addition, a lower unit price may reflect a lower quality of the product. In the automotive supply chain, component quality is crucial to vehicle safety and reliability. If a company chooses a supplier that offers a very competitive price but delivers poor quality or defective products, the costs for handling returns, repairs or replacing suppliers can increase significantly in the long term. In extreme cases, such as Ford’s reliance on Chinese suppliers to reduce costs, poor quality of components led to additional costs for handling returns and finding new suppliers (Katsaliaki, Galetsi, & Kumar, 2022).

Therefore, in the analysis of unit price, it is essential to consider also the trade-off between cost, quality and punctuality of deliveries. The focus should not be only on the lowest price, but on choosing suppliers that guarantee a balance between these elements, minimizing risks for the supply chain and ensuring continuity and production efficiency.

3.4.5 Quantity received

The quantity required is a crucial factor in supply chain management, as it directly affects a company’s ability to maintain production and optimize operating costs. Calculating the exact quantity required is crucial to ensure uninterrupted production, avoiding both shortages and overstocks. As highlighted by Dolgui, Grimaud and Shchamialiova (2010), an effective management of the required quantities allows to balance the availability of raw materials or finished products with the production needs, reducing the risks of production downtime and the costs associated with storing unused stocks. (Dolgui, Grimaud, & Shchamialiova, 2010)

Similarly, delivery time, or lead time, is also closely related to the supplier's position in the supply chain. It is logical to understand that, in the case of a supplier located at a considerable distance, it is preferable to order larger quantities to compensate for transport costs and better exploit economies of scale. In many cases, the supplier may also require larger orders to justify sending a shipment. As a result, careful management of routine quantities and lead time is essential to reduce overall inventory costs and ensure production efficiency.

It is therefore necessary to calculate precisely the optimum quantity to be ordered, taking into account various factors such as expected demand, distance from the supplier, delivery times and storage costs. This balance allows not only to minimize the costs related to excess or insufficient inventory, but also to improve the fluidity of the production process, ensuring a greater competitiveness of the company on the market.

3.4.6 Quantity discrepancy

This variable represents the variance between the quantity requested from the supplier and the quantity actually received. Both excess and shortages of products pose challenges for the company. In the former case, production may be impacted, while in the latter, inventory costs are likely to increase. Consequently, this variable often represents one of the primary sources of inefficiency in the supply chain.

Quantity discrepancies can be attributed to various factors, including delivery errors, logistical issues, or limitations in the supplier's production capacity. These inefficiencies force companies to resort to emergency supplies or revise production plans, both of which are costly options.

Internationalization of the supply chain also presents a constraint. Suppliers located far away are more prone to delivery errors due to the coordination required between different means of transport. Additionally, companies have less control over distant suppliers, making it more challenging to address these errors in real time.

3.4.7 Total Cost of the Order

The total cost of an order includes different components apart from the unit price of goods, encompassing both direct and indirect costs. The first category consists of transportation costs and customs costs, while the second involves expenses related to risk management, stock management, and operational inefficiencies. This indicator provides a comprehensive view of the economic performance of the whole supply chain, which is a crucial objective for companies to pursue. To achieve this, they focus on techniques such as global sourcing, supply contract negotiation, and optimization of transport routes. For instance, BMW and many other companies have chosen to optimize transportation routes of suppliers from around the world (Holweg & Pil, 2004).

3.4.8 Time Offset

The time offset reflects the variance between the actual delivery and the expected delivery, serving as an indicator of supplier punctuality. Both delays and early deliveries can have negative impacts on the production process. In the case of delays, there is a direct impact on production, with the risk of not delivering the product to the customer on time, potentially tarnishing the company's image and reducing its market efficiency (Pai, Hebbar, & Rodrigues, 2015). Conversely, early deliveries pose a risk mainly to inventory management, as many companies aim to minimize stock using a Just In Time approach, thus potentially incurring high inventory costs.

To address this issue, many companies implement strategies such as advanced planning, establishing safety buffers, and diversifying supply sources. Other monitoring tools for this variable include real-time tracking systems which facilitate rapid intervention, particularly in case of delays.

3.5 Conclusion

In this chapter, we have analyzed several variables that demonstrate the importance for car manufacturers to diligently monitor their suppliers and optimize logistic operations. Distance can lead to increased costs and delays, as well as extended lead times, necessitating careful management of stocks to prevent obsolescence and high inventory costs. The product category, unit price of goods, and quantity required directly impact the choice of supply and storage strategies. Additionally, quantity discrepancies and time offsets underscore the importance of maintaining a flexible supply chain capable of quickly adapting to unforeseen events and changes in demand.

In conclusion, to survive the high competitiveness of the automotive supply chain, it is fundamental for a car manufacturer to carefully consider all these variables. It is crucial for the prosperity of a company to balance costs, risks, and performance, ensuring continuity in production and a rapid response to every change in the sector. All of these are fundamental elements for the long-term success of a company.

4. Empirical Analysis

4.1 General regression model

This document analyzes, using regression analysis and ANOVA, how some continuous and categorical variables influence the time offset.

Minitab automatically excluded from the analysis the variable “quantity requested”; this decision is likely due to multicollinearity with another variable.

This finding will be justified by the analysis of the correlation and by the regression analysis.

Correlation Matrix

	DISTANCE (km)	**LEAD TIME (gg)**	**PRICE U (€)**	**ORDER COST (€)**	**Q. REC**	**Q. REQ**
LEAD TIME (gg)	0.952					
PRICE U (€)	0.173	0.188				
ORDER COST (€)	0.383	0.363	0.876			
Q. RECEIVED	-0.187	-0.135	-0.219	-0.191		
Q. REQUESTED	-0.176	-0.126	-0.213	-0.187	0.931	
Q. DISCR ASS	-0.088	-0.061	-0.067	-0.074	0.217	0.406

Table 1: Correlation matrix between independent variables

From the table reported above, all the correlations between the continuous variables are derived.

Of particular importance is the very high relation between “quantity received” and “quantity requested” (correlation coefficient of 0.931) and this could indicate a potential issue of multicollinearity between variables. Due to this phenomenon Minitab decided automatically to exclude one of the two predictors from the analysis. However, the exclusion of one of the two variables from the model does not change the result. This assumption can be confirmed by the regression analysis, as the output obtained using "quantity requested" rather than "quantity received" are almost equal. (The demonstration below)

Coefficients (EXCLUSION of quantity requested)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.915	0.173	5.28	0.000	
DISTANCE (km)	0.000046	0.000223	0.21	0.835	12.49
LEAD TIME (gg)	0.1514	0.0631	2.40	0.017	11.36
PRICE U (€)	0.0107	0.00865	1.24	0.217	5.33
COST OF THE ORDER (€)	-0.000078	0.000048	-1.61	0.108	5.87
QUANTITY RECEIVED	0.000098	0.000072	1.37	0.172	1.16
QUANTITY DISCREPANCY ASS	-0.000178	0.000185	-0.96	0.337	1.05

Table 2: Coefficients table obtained not considering the variable "quantity requested"

Coefficients (EXCLUSION of quantity received)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.916	0.17	5.38	0.000	
DISTANCE (km)	0.000045	0.000222	0.20	0.840	12.39
LEAD TIME (gg)	0.1516	0.0629	2.41	0.016	11.31
PRICE U (€)	0.01077	0.00864	1.25	0.213	5.32
COST OF THE ORDER (€)	-0.000078	0.000048	-1.62	0.107	5.86
QUANTITY REQUESTED	0.000109	0.000074	1.47	0.141	1.31
QUANTITY DISCREPANCY ASS	-0.000243	0.000197	-1.23	0.218	1.2

Table 3: Coefficients table obtained not considering the variable "quantity received"

Observing the results obtained it is possible to confirm that the scenario is the same and so it would be indifferent to choose between the two variables. Hence, it has been randomly selected as the indicator "quantity received".

Returning to the analysis of correlations, it is evident that another pair of predictors which show a strong correlation are "price" and "cost of the order", with a coefficient of 0.876. The same happens for "lead time" and "distance", with a coefficient equal to 0.952. These results should be investigated afterward because they could suggest a problem of multicollinearity.

Given the assumption made above the following variables have been chosen to construct the model:

Scenario with dependent variable = TIME OFFSET ASS, independent variables = DISTANCE, LEAD TIME, PRICE, COST OF THE ORDER, QUANTITY RECEIVED, QUANTITY DISCREPANCY

Regression Equation

TIME OFFSET ASS (gg)	=	0.915 + 0.000046 DISTANCE (km) + 0.1514 LEAD TIME (gg)
		+ 0.01070 PRICE U (€) - 0.000078 COST OF THE ORDER (€)
		+ 0.000098 QUANTITY RECEIVED - 0.000178 QUANTITY DISCREPANCY ASS

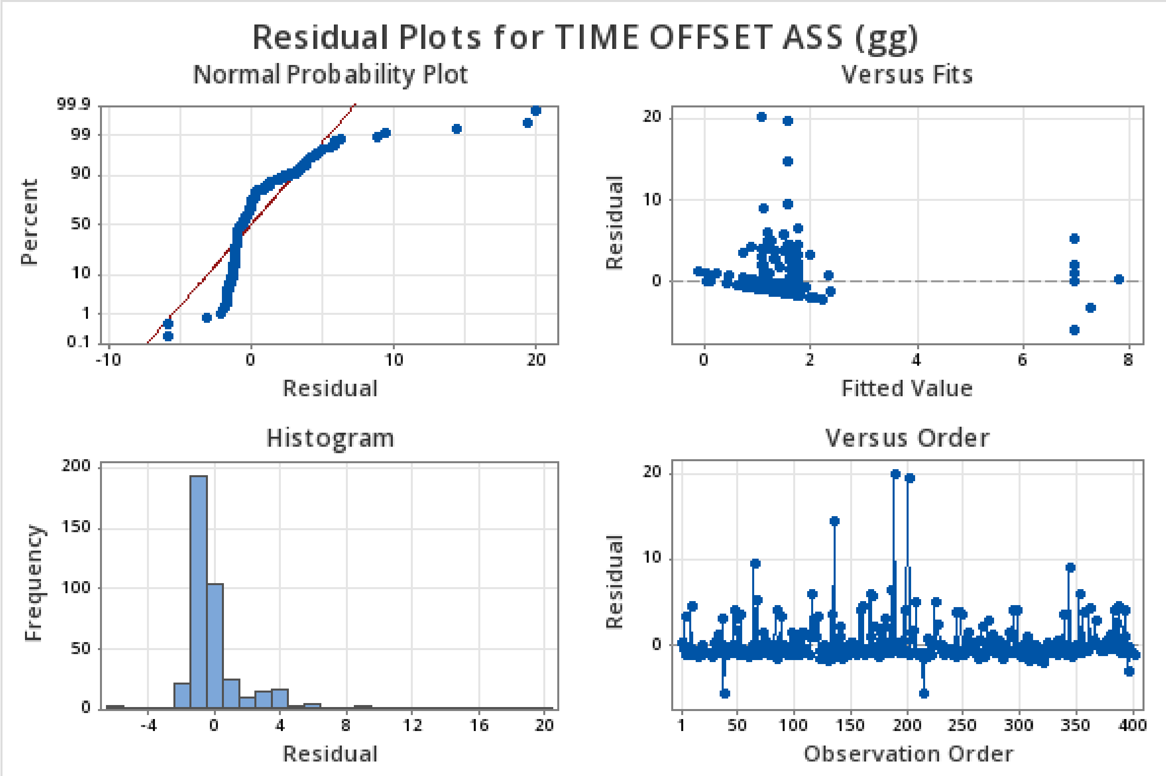

Figure 2: Residual plot graphs – First scenario

After analyzing the residual plot graphs, it's evident that the model cannot be considered valid because one or more fundamental assumptions are not met.

Let's analyze each graph more specifically:

- Normal probability plot: this plot shows residuals in relation to the normal distribution. Ideally, all the points should follow a straight line. However, in this case, the assumption is not confirmed, and there are several points noticeably detached from the line, indicating deviation from normality.
- Histogram: the ideal graph should display a bell-shaped curve centered at zero. However, in this instance, the curve is skewed to the right, further reinforcing that the normality assumption is not upheld.
- Residual vs. fit: theoretically, residuals should be randomly distributed around zero without any discernible pattern. Nevertheless, in this case, the majority of the points are concentrated around lower fitted values, with some large residuals at both ends, signifying the absence of linearity between the variables.

- Residual vs. order: similar to the residual vs. fit graph, residuals should follow a random pattern. Once again, this expectation is not fulfilled, indicating the possibility of autocorrelation between the residuals.

It is crucial to start by analyzing the coefficients table to understand which variables are more significant than others in the model and to identify potential multicollinearity issues that could influence the validity of the analysis.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.915	0.173	5.28	0.000	
DISTANCE (km)	0.000046	0.000223	0.21	0.835	12.49
LEAD TIME (gg)	0.1514	0.0631	2.40	0.017	11.36
PRICE U (€)	0.0107	0.00865	1.24	0.217	5.33
COST OF THE ORDER (€)	-0.000078	0.000048	-1.61	0.108	5.87
QUANTITY RECEIVED	0.000098	0.000072	1.37	0.172	1.16
QUANTITY DISCREPANCY ASS	-0.000178	0.000185	-0.96	0.337	1.05

Table 4: Coefficients table – First scenario

The "Coeff" column shows the relationships between the dependent variable and the independent variables.

The "SE Coef" column indicates the precision of the model. All the values are small, indicating that the model is generally precise in estimating the coefficients.

The t-value and p-value columns are used to analyze how a predictor influences the dependent variable.

However, the model is not suitable for valid analysis. The only significant indicator is "lead time", with a high t-value and a p-value close to zero, but it has a major issue of multicollinearity as the VIF value is higher than 10.

All the other variables seem not to be statistically insignificant, as their p-values are higher than 0.05. Additionally, most of them have an issue of multicollinearity, except for "quantity received" and "quantity discrepancy".

However, it is not possible to analyze the meaning of the positive relationship between "lead time" and "time offset" because this indicator has a value that is set by the company, and therefore is not considerable as a variable because its value is fixed for each supplier and consequently for the associated orders. Nevertheless, it is evident that suppliers located far away tend to have longer lead times compared to those closer in the supply chain.

At this point, it is possible to try to exclude some variables from the analysis in the hope of obtaining a better model. Certainly, the first indicator to be excluded is "lead time" for two main reasons:

1. The data it represents have all been set by the company and during the construction of the database, they have only been used in some cases to calculate the time offset.

2. It displays a significant problem of multicollinearity because the VIF value is higher than 11. This problem could arise due to the strong relation with the variable "distance", as shown by the correlation coefficient equal to 0.952.

To verify these assumptions, the variable "lead time" will be removed from the analysis, and the new model will be studied.

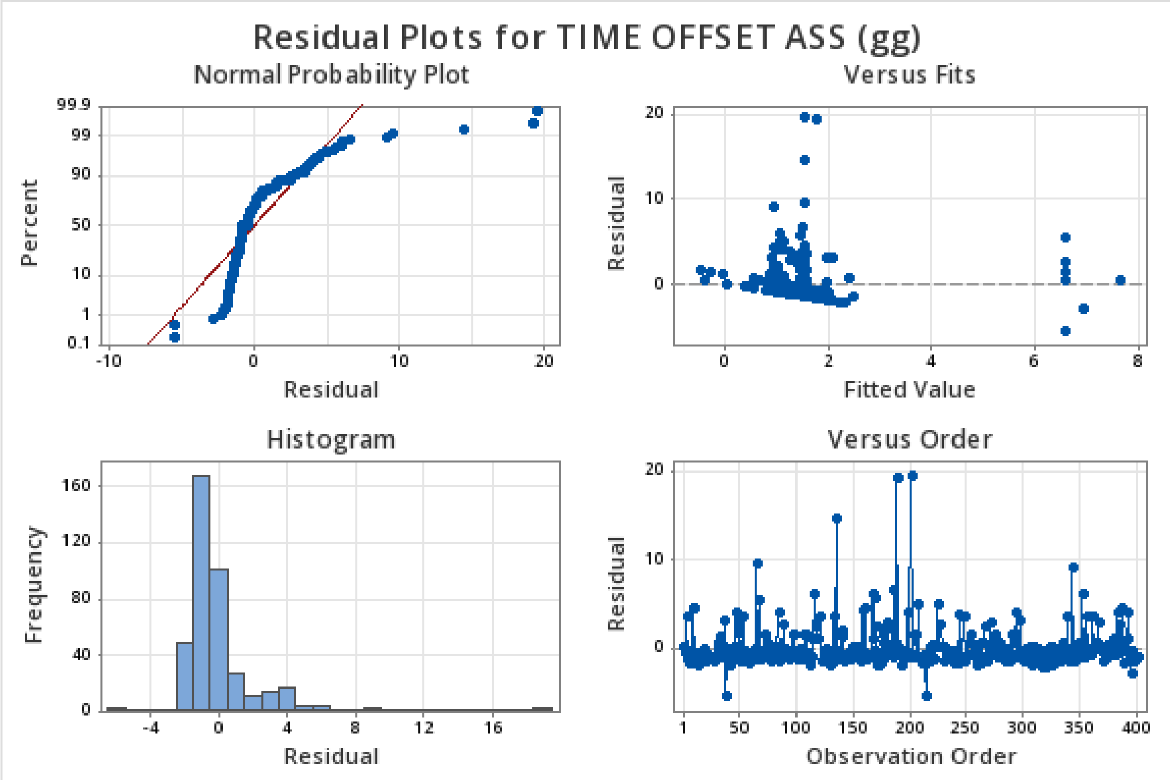

Figure 3: Residual plot graphs – Second scenario

Analyzing the graphs below, it can be inferred that all the conclusions made for the initial scenario still hold, however it is necessary to consider also in this case the coefficients table because in this way it is possible to further deleting other variables not useful for the analysis.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.882	0.174	5.08	0.000	
DISTANCE (km)	0.000549	0.000075	7.34	0.000	1.40
PRICE U (€)	0.01509	0.00851	1.77	0.077	5.10
COST OF THE ORDER (€)	-0.000099	0.000048	-2.07	0.039	5.68
QUANTITY RECEIVED	0.000127	0.000071	1.78	0.076	1.13
QUANTITY DISCREPANCY ASS	-0.000156	0.000186	-0.84	0.400	1.05

Table 5: Coefficients table – Second scenario

In the new model, two variables are found to be statistically significant: "distance" and "cost of the order". Their p-values are lower than 0.05, and their t-values are high.

There is a positive relationship between "time offset ass" and the variable "distance". This aligns with expectations, as it is reasonable to assume that a greater distance between suppliers and the company can lead to delays or advances in orders.

In the case of the "cost of the order" variable, the relationship is not very significant. This is likely due to the fact that the indicator is derived from the product of price and quantity. As explained earlier, since the two variables are expected to have opposite trends (a negative relationship between price and time offset and a positive relationship between quantity and time offset), this could impact the behavior of the "cost of the order" and distort the results.

All the previous observations regarding the Coeff and the SE Coeff remain applicable.

In conclusion, the model developed without considering the variable "lead time" is certainly an improvement compared to the previous one.

In this analysis it emerges that the issue of multicollinearity has not been completely solved, and there are still two variables which display high VIF values: "price" and "cost of the order". Therefore, in order to make the analysis more valid, it would be better to exclude one of the two variables.

The t-value and p-value reveal that "price" is not statistically significant, and so it would apparently be better to exclude this indicator from the model. However, as explained in the analysis of the coefficient table, the variable "cost of the order" is not significant. Therefore, it would be more effective not to consider this predictor, even though this could mean losing another significant variable.

The model obtained excluding "cost of the order" is the following:

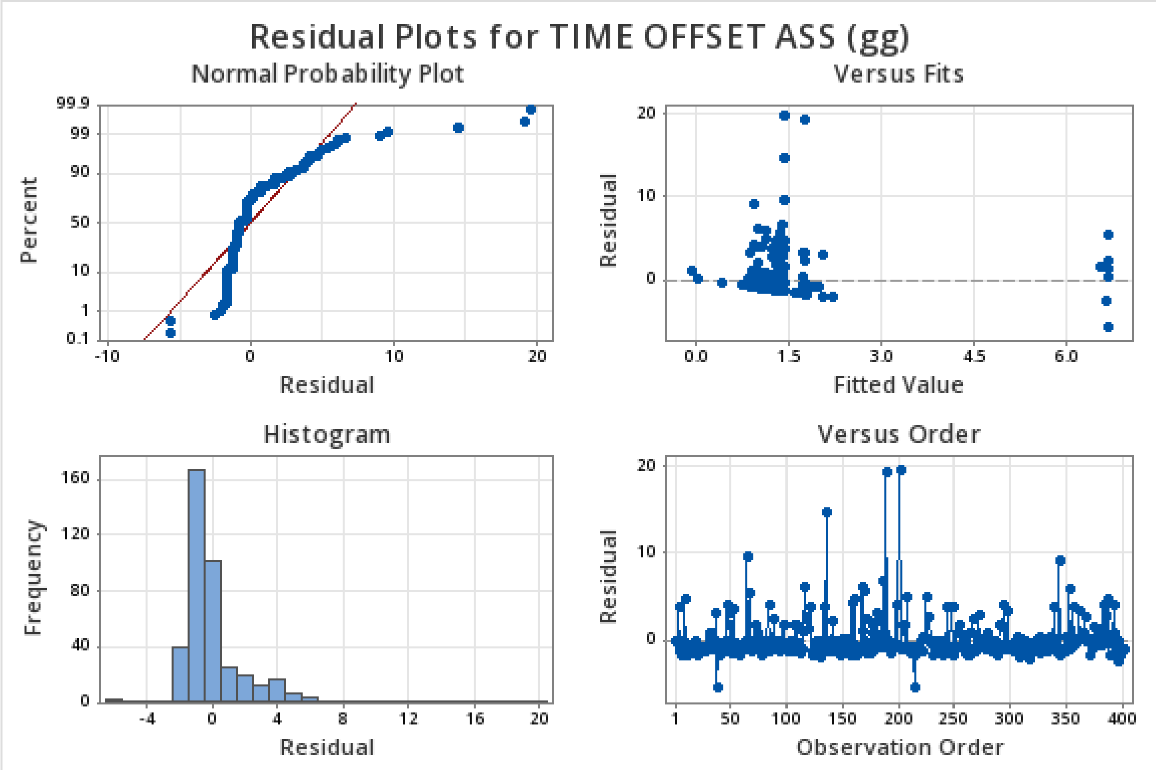

Figure 4: Residual plot graphs – Third scenario

The graphs are quite similar to the ones observed before, so it can be concluded that the model is still not adequate.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.857	0.174	4.92	0.000	
DISTANCE (km)	0.000473	0.000065	7.22	0.000	1.06
PRICE U (€)	-0.00060	0.00392	-0.15	0.879	1.07
QUANTITY RECEIVED	0.000113	0.000071	1.59	0.112	1.12
QUANTITY DISCREPANCY ASS	-0.000152	0.000186	-0.82	0.415	1.05

Table 6: Coefficients table – Third scenario

As expected, the problem of multicollinearity has been completely solved but the model has lost another statistically significant variable and the only remaining one is “distance”.

Since this model is not very significant, it is now possible to proceed with the elimination of some outliers, which are one of the main causes of lack of accuracy. However, before it must be decided which model between the last two can be considered as the most adequate in order to understand which variables will compose the final scenario.

It is necessary to analyze both because they have as well some pros and cons that need to be evaluated:

- Model 1 has a higher number of significant variables as both “distance” and “cost of the order” have a p-value lower than zero associated with a high t-value. However, it displays a huge problem of multicollinearity (VIF value of “price” = 5.10 and VIF value of “cost of the order” = 5.68).
- Model 2 does not display the issue of multicollinearity, but it contains just one relevant indicator and has lost a statistically significant variable with respect to model 1, which is “cost of the order”. However, as already explained, this predictor is not valid for the purpose of the analysis and so it is not fundamental to consider it to obtain a more precise model.

In conclusion, the second scenario can be considered the better one as it resolves the problem of multicollinearity, it is simpler to be interpreted, it does not consider a variable which anyway is not useful for the study and quite all the relationships have the expected sign of the coefficient.

The first part of the analysis has been concluded and the variables which will compose the final model have been selected.

In summary, the initial model revealed a significant issue related to multicollinearity between two pairs of variables: "distance" and "lead time", "price" and "cost of the order". To address this problem, a decision was made based not on statistical rules, but on a thorough consideration of how the variables were handled in the database and how the data pertaining to these indicators were derived. It became apparent that both the “lead time” and the “cost of the order” were not particularly significant. The exclusion of these variables solved one of the main lack of accuracy of the model, due to the presence of a huge problem of multicollinearity, as four variables out of six had a VIF value higher than 5.

It is now crucial to remove outliers in order to obtain the best possible model.

Analyzing box plot graphs can help identify these extreme points. It has been assumed as a general rule to delete 25% of the data present at the extremes, so in this case the points which are far away from the median (blue rectangle). Given that the initial database is composed of 400 values, it is possible to delete up to 100 points.

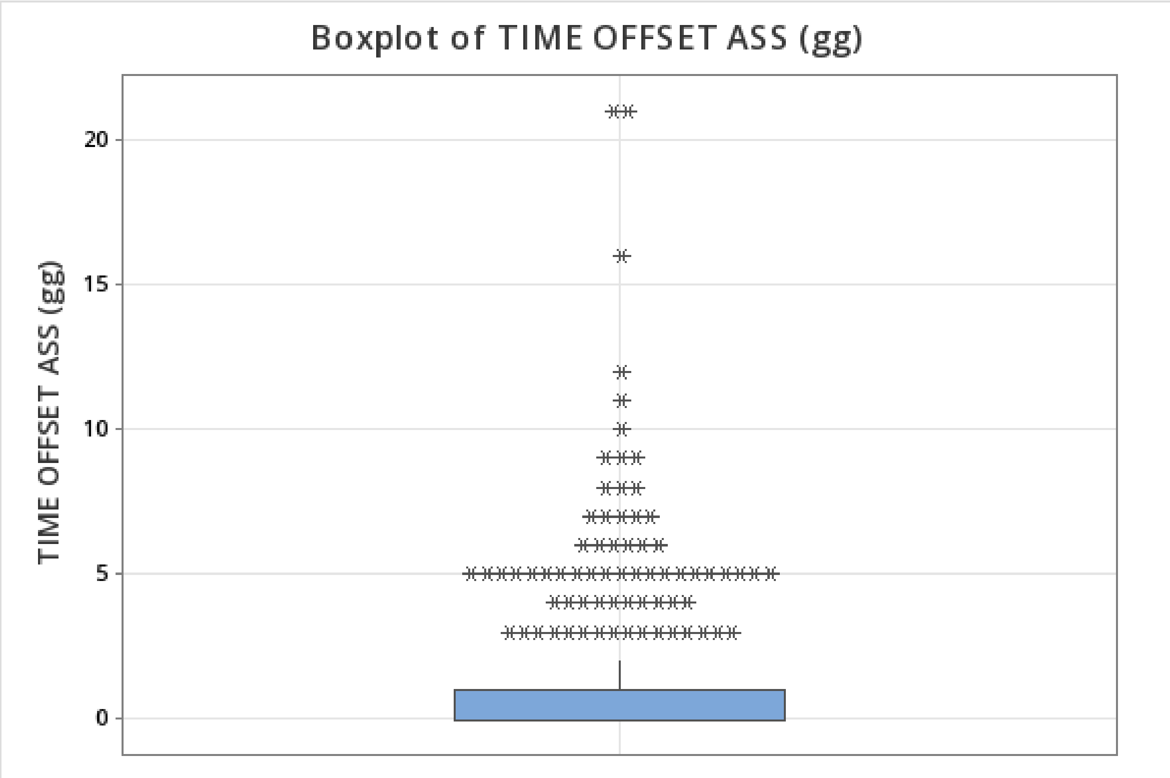

Figure 5: Box plot graph – Time offset

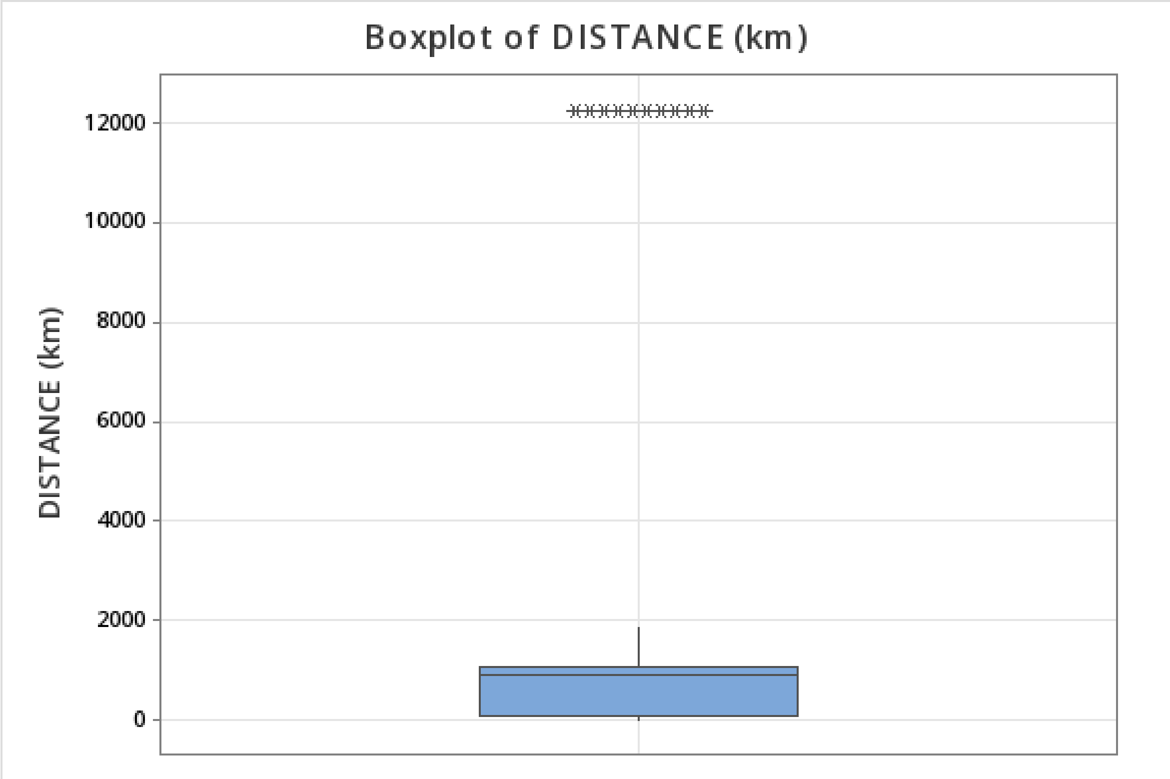

Figure 6: Box plot graph - Distance

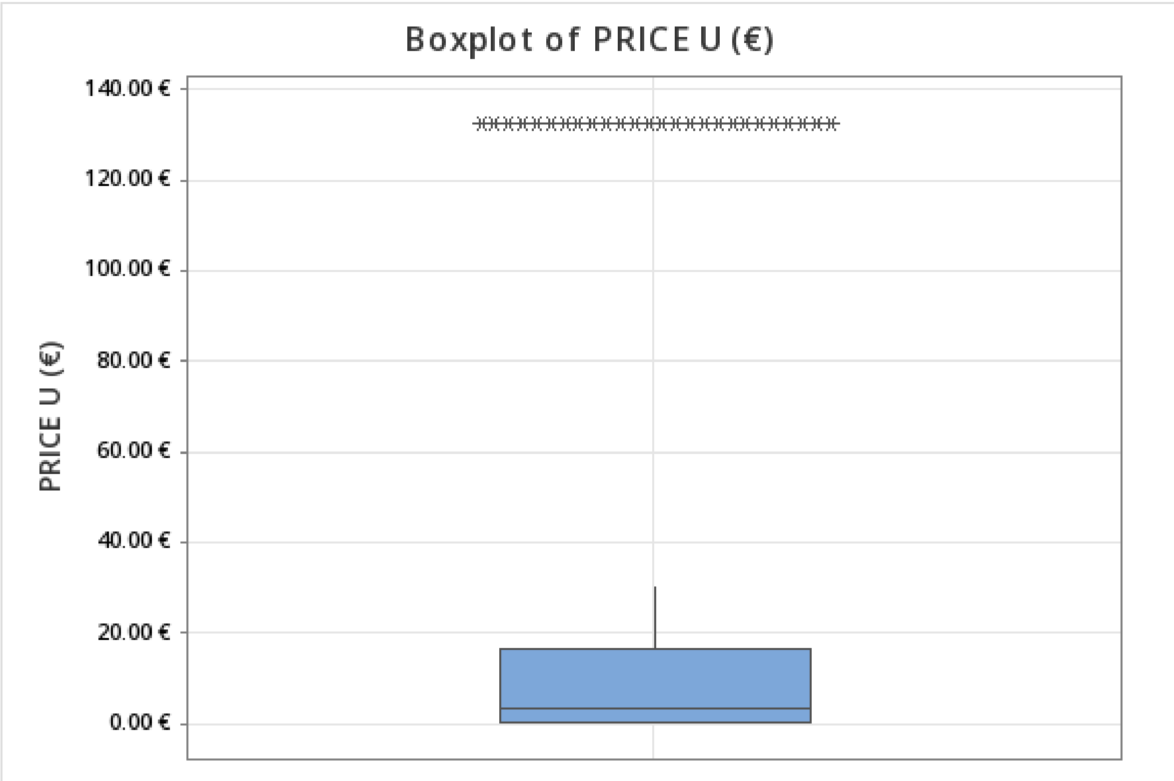

Figure 7: Box plot graph – Price U

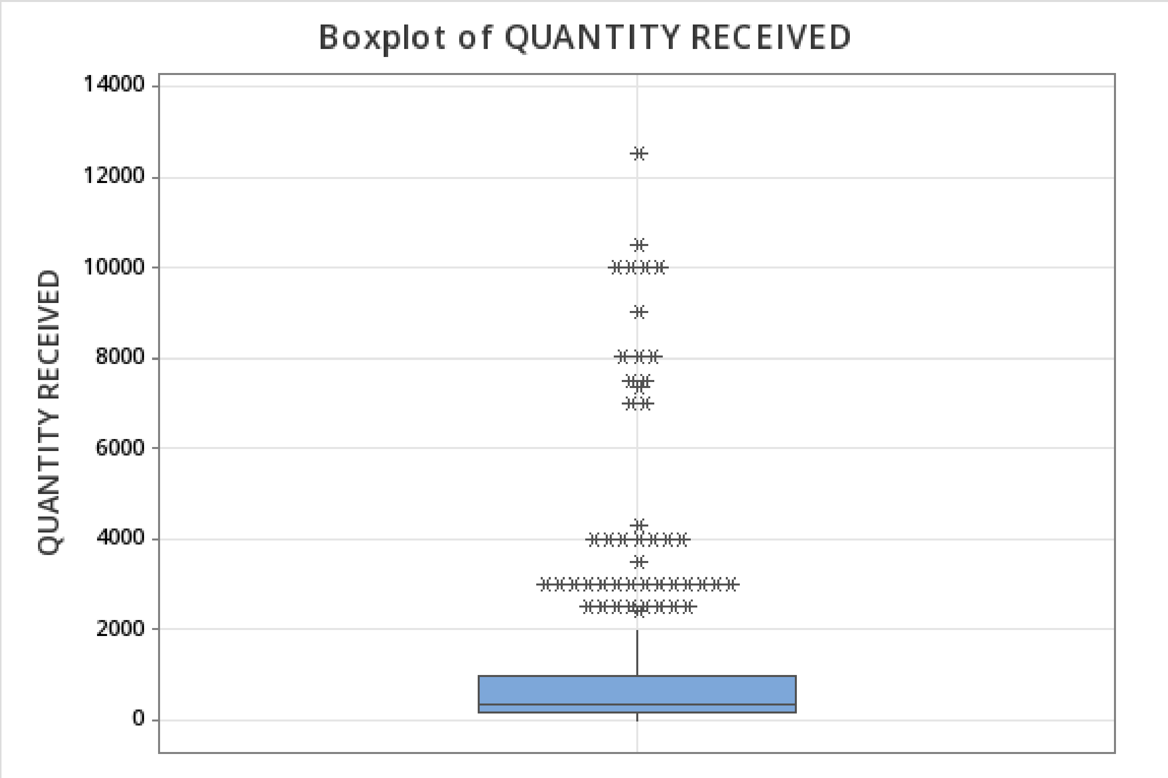

Figure 8: Box plot graph – Quantity received

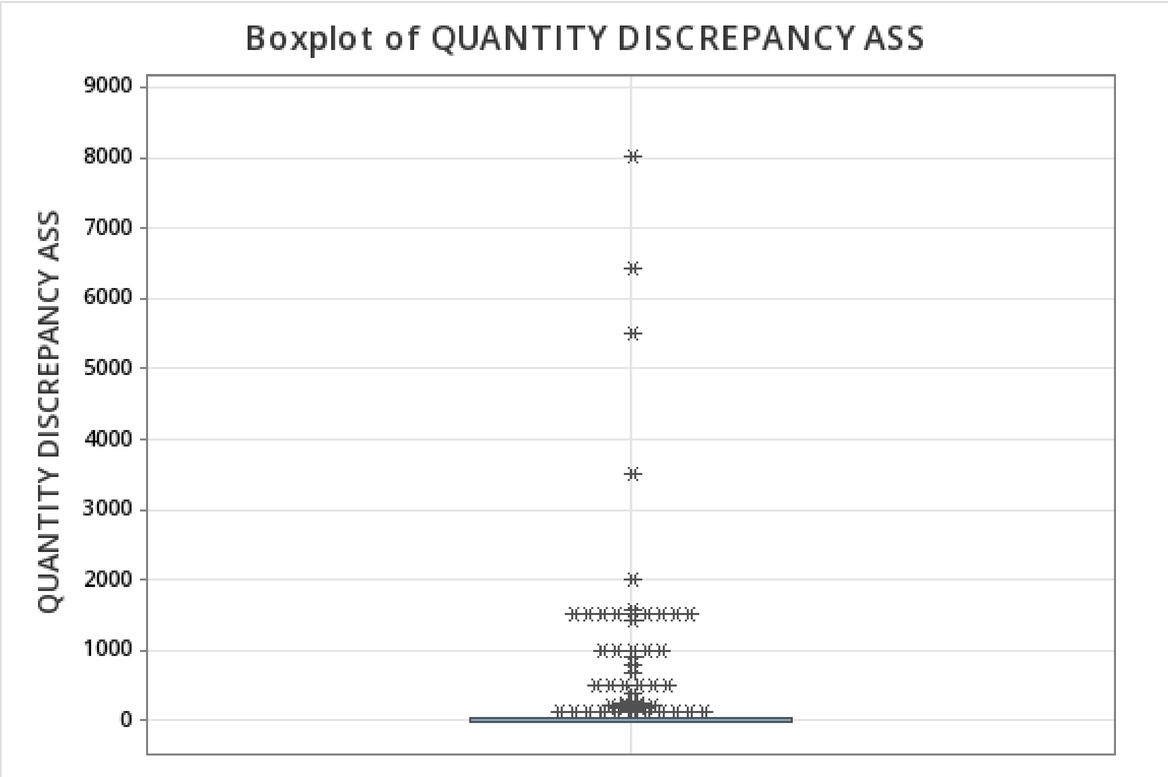

Figure 9: Box plot graph – Quantity discrepancy

The new model obtained is the following one: 37 values have been deleted, the 9,25% of the initial model.

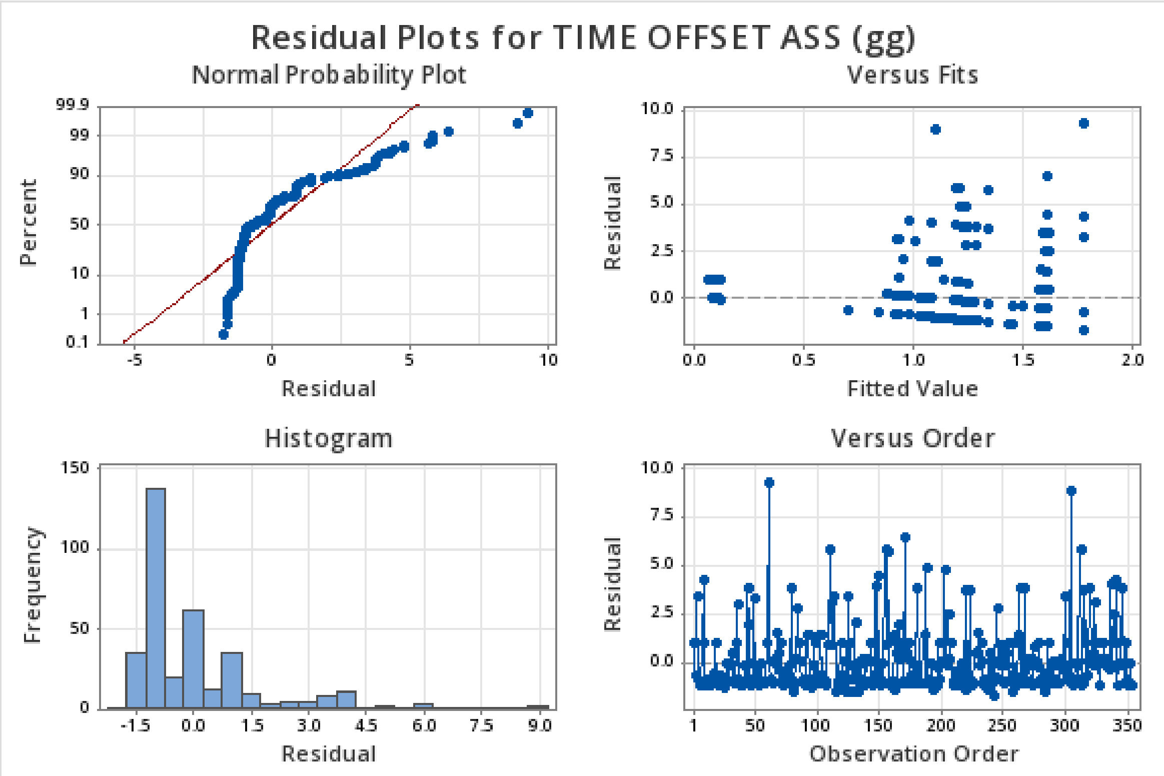

Figure 10: Residual plot graphs – Final scenario

Analyzing the residual plot graphs, it can be stated that this model is quite accurate.

- Normal probability plot: as previously explained all the points should follow the straight line, and this assumption is mainly confirmed.
- Histogram: residuals are ideally distributed, showing a symmetrical bell shape (as it is expected). Again, the assumption of normality is confirmed.
- Residual vs. fit: in general, the residuals are casually distributed around zero without any evident pattern, confirming the absence of autocorrelation.
- Residual vs. order: similar to the residual vs. fit, residuals should be distributed following a random pattern. Once again, the expectation is confirmed, suggesting that there is no autocorrelation between residuals.

Given that all assumptions are met, it is now possible to conclude that the regression analysis model is adequate and its results are valid.

To sum up:

- All the relations between variables are linear.
- Residuals are independent.
- Variance in residuals is constant.
- Residuals follow a normal distribution.

These facts ensure reliable estimates and accurate predictions, enhancing the understanding of the studied phenomenon.

It is now possible to start with the analysis of the single variables, in order to study the relations between them.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	1.091	0.237	4.60	0.000	
DISTANCE (km)	0.001128	0.00028	4.03	0.000	2.06
PRICE U (€)	-0.0916	0.0201	-4.55	0.000	1.95
QUANTITY RECEIVED	0.000064	0.000075	0.86	0.388	1.26
QUANTITY DISCREPANCY ASS	-0.000176	0.000183	-0.96	0.338	1.06

Table 7: Coefficients table – Final scenario

Comparing the new model with the previous one it is possible to note that the only two statistically significant variables are “distance” and “price” (p-value lower than 0.05 and high t-value). An important difference with respect to the previous analysis can be evidenced: the indicator “price” has become statistically significant, with a p-value lower than 0.05 associated with a high t-value. It is reasonable to assume that a higher price is also associated with better order punctuality, since any delay affects production by reducing its efficiency and advance deliveries may also be a problem, especially for companies that adopt policies such as Just In Time and therefore aim to keep a low level of stock.

Instead “quantity received” and “quantity discrepancy” still remain not statistically significant and are consequently useless to the analysis.

Model Summary

Metric	Value
S	2.36244
R-sq	6.37%
R-sq(adj)	5.33%
R-sq(pred)	4.15%

Table 8: Model summary – Final scenario

The reported Model Summary presents some key indicators to assess the quality of the regression model.

- The S value represents the standard error of the residuals and indicates how far the values predicted by the model deviate from the observed values. A lower value of S indicates better predictive precision of the model.
- R-sq value indicates the percentage of the total variability of the dependent variable explained by the model, in this case the value is equal to 6.37% and this suggests that most of the variability of the phenomenon is not explained by the independent variables included in the scenario. This may indicate the need to consider additional explanatory variables or to adopt a more complex model.
- R-sq(adj) is equal to 5.33% value, indicating that some variables in the model do not add a significant contribution to the explanation of the phenomenon.
- R-sq(pred) evaluates how well the model could make predictions on new data. Such a low predicted R-sq indicates that the model does not generalize well and may not be reliable for making future predictions.

The R-sq value of 6.37% indicates that the independent variables used in the model (distance, price, quantity received and quantity discrepancy) explain only a small part of the variability of the time offset. This may be due to several factors specific to the sector under consideration.

Firstly, the automotive sector is particularly complex and subjected to numerous external factors which can influence suppliers' delivery precision. For example customs delays, changes in international regulations, global crises (such as pandemics or wars) and problems in the global supply chain (such as the semiconductor crisis) can have a significant impact on the precision of deliveries, but these factors can not be included in the model because they are very difficult to be calculated in a concrete way.

In addition, the automotive sector is heavily dependent on a highly interconnected supply chain on a global scale, where even small disruptions at one point of the chain can have cascading effects on delivery times.

Finally, the reduction in data in the database may have affected the result. The deletion of data may have reduced the representativeness of the sample, and if the deleted data included extreme or influential values, the current model may no longer capture some important dynamics.

In conclusion, the low R-sq reflects the complexity of the automotive industry and the difficulty of fully modelling all the factors that influence the dependent variable in such a changing and unpredictable global environment.

In this study a 95% confidence interval was used, corresponding to a significance level (alpha) of 5%. This means that you accept a 5% chance of making an error of type I, or to conclude that there is an effect when in fact there is none. This approach implies that, if the study were repeated, 95% of the ranges would contain the true value of the parameter.

However, the database only includes two product categories: smallware and electronics. These two types of products are characterized by significantly different prices and quantities. For example, a screw will have a completely different cost compared to an electrical circuit and the price will be really low. Additionally, the lots of smallware will likely be very large, while in the case of electrical circuits, they are smaller. It is thus difficult to compare these two categories, and for a more precise analysis it would be better to split the database, obtaining then two new databases composed of 151 data in the case of the electronics category and 213 data in the case of smallware category. However, this would likely result in a loss of accuracy since the data will be split down the middle.

4.1 Electronics analysis

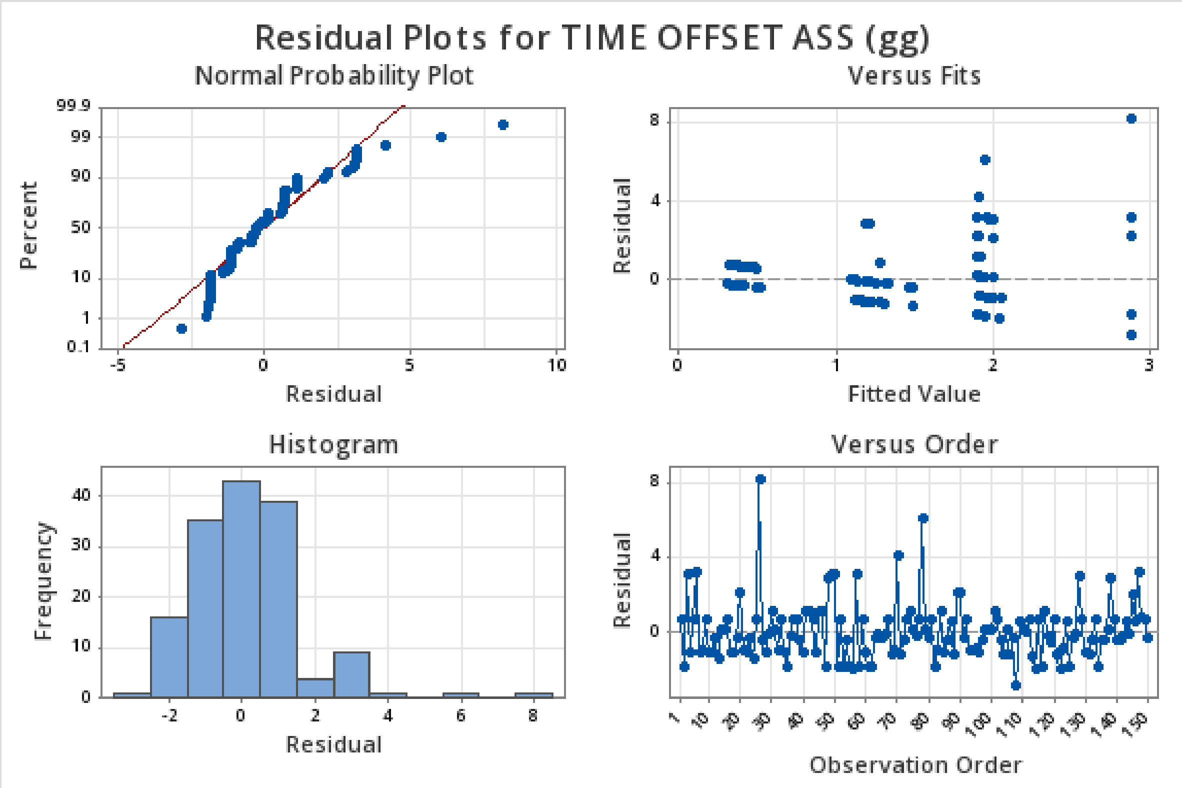

Figure 11: Residual plot graphs – Electronics category

The assumption of normality is respected, as both the normal probability plot and the histogram display the expected distributions. Also, the residual vs order shows a random pattern, except for some outliers that are still present, which confirm the absence of autocorrelation. The only graph that displays some problems is the residual vs fit, which seems to present a descendent pattern of the values, and this distribution can indicate some issue related to the absence of linearity. However, this pattern can be due to the presence of remaining outliers that can not be deleted because removing too many outliers can distort results, lead to loss of important information, and compromise the model's ability to generalize.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	3.30	3.48	0.95	0.345	
DISTANCE (km)	-0.00105	0.0031	-0.34	0.734	3.22
PRICE U (€)	-0.0852	0.0246	-3.46	0.001	2.90

QUANTITY RECEIVED	0.000447	0.000594	0.75	0.453	1.98
QUANTITY DISCREPANCY ASS	0.00022	0.00233	0.09	0.926	1.03

Table 9: Coefficients table – Electronics category

According to the coefficient table, it is evident that the only statistically significant variable is "price”, as it has a p-value close to zero and a t-value higher than 3. As expected, it exhibits a negative relationship with the dependent variable. However, the VIF values for "distance" and "price," which are around 3, indicate a potential issue of multicollinearity between the two variables. To determine if distance can have a significant impact on the analysis, another regression model excluding the variable "price" can be constructed to further explore other potential relationships between the variables under consideration and the dependent variable.

Model Summary

Metric	**Value**
S	1.56919
R-sq	19.32%
R-sq(adj)	17.10%
R-sq(pred)	11.78%

Table 10: Model summary – Electronics category

The R-squared values for the electronics category are significantly higher than those of the general model. This might be due to structural differences between the two product categories in the original database. The dynamics between independent variables have different impacts on the time offset for each product category. When data from both categories are combined in a single model, these structural differences may decrease the model's ability to explain variability in the dependent variable.

Creating separate regression models for each category allowed for a better understanding of the specific characteristics of each category. Consequently, the model for each individual category can explain a larger portion of the time offset variability.

Furthermore, dividing the categories reduced the noise caused by variability between products, resulting in a more consistent dataset. This allows the model to accurately capture the relationships between independent variables and the time offset.

Now, let's analyze the new model obtained by excluding the variable "price" to determine if other variables have become more significant.

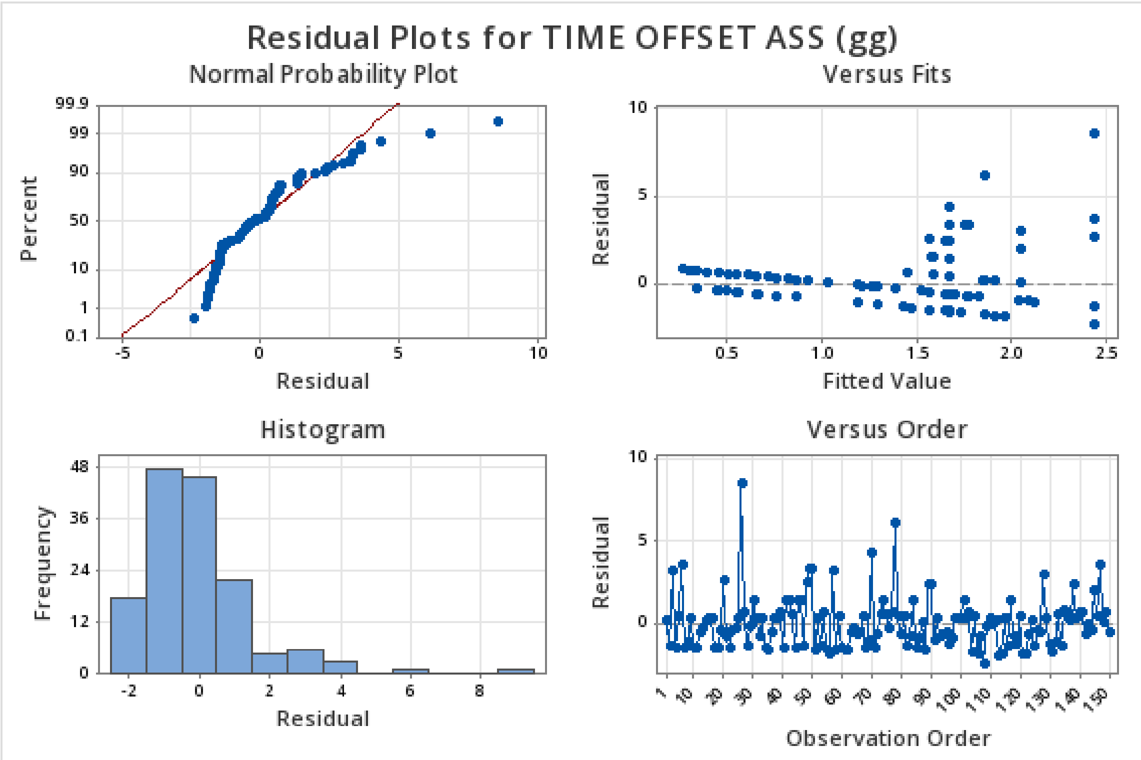

Figure 12: Residual plot graphs – exclusion of variable "Price U"

From the analysis of the residual plot graphs it is possible to see that all the assumptions still hold, and that the residual vs fit graph has slightly improved, showing now a more random distribution of the residuals.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-6.70	2.02	-3.33	0.001	
DISTANCE (km)	0.00751	0.00194	3.87	0.000	1.17
QUANTITY RECEIVED	0.001756	0.000475	3.69	0.000	1.18

QUANTITY DISCREPANCY ASS	-0.00082	0.0024	-0.34	0.731	1.01

Table 11: Coefficients table – exclusion of variable "Price U"

After the exclusion of the variable "price" from the analysis, two other indicators have become statistically significant: "distance" and "quantity received".

It is of particular interest that the variable "quantity received" is now significant, which was not the case in the analysis where the general database was considered. As expected, the relation with "time offset" is positive since it is possible to imagine how with large volume orders, the preparation times are longer because it takes more time to handle the goods. This has a negative impact on delivery times. In addition, logistics coordination becomes more complex with larger quantities as the transport of larger lots requires more careful planning, with potential delays due to the need to consolidate shipments and use more capacity transport resources.

The supplier's production capacity may be another key factor: very large orders can overload production, leading to longer completion times and, as a result, delays. Finally, transit times can also be affected, as large quantities of transport are more likely to cause logistical problems. In summary, the increase in the quantity delivered amplifies the management and operational difficulties, causing a direct increase in delays in deliveries.

Model Summary

Metric	Value
S	1.62717
R-sq	12.65%
R-sq(adj)	10.86%
R-sq(pred)	5.77%

Table 12: Model summary – Exclusion of the variable "Price U"

The variable that was eliminated was initially significant. However, upon removal, two other variables became significant. This phenomenon can occur when there is a multicollinearity issue between the indicators, as previously evidenced. In the presence of this problem, a significant variable can reduce the impact of other predictors, making them appear nonsignificant in the model. By removing this variable, the others can better express their effect on the time offset and become significant.

However, the values of R-sq, R-sq(adj) and R-sq(pred) show that the overall ability of the model to explain time offset variability has decreased compared to the previous version. This indicates that although other variables have become significant, the removed variable played an important role in improving the explanatory power of the model. In fact, removing a significant variable has reduced the ability of the model to capture total variability, although new significant variables can now contribute more clearly to the interpretation of the time offset.

4.2 Smallware analysis

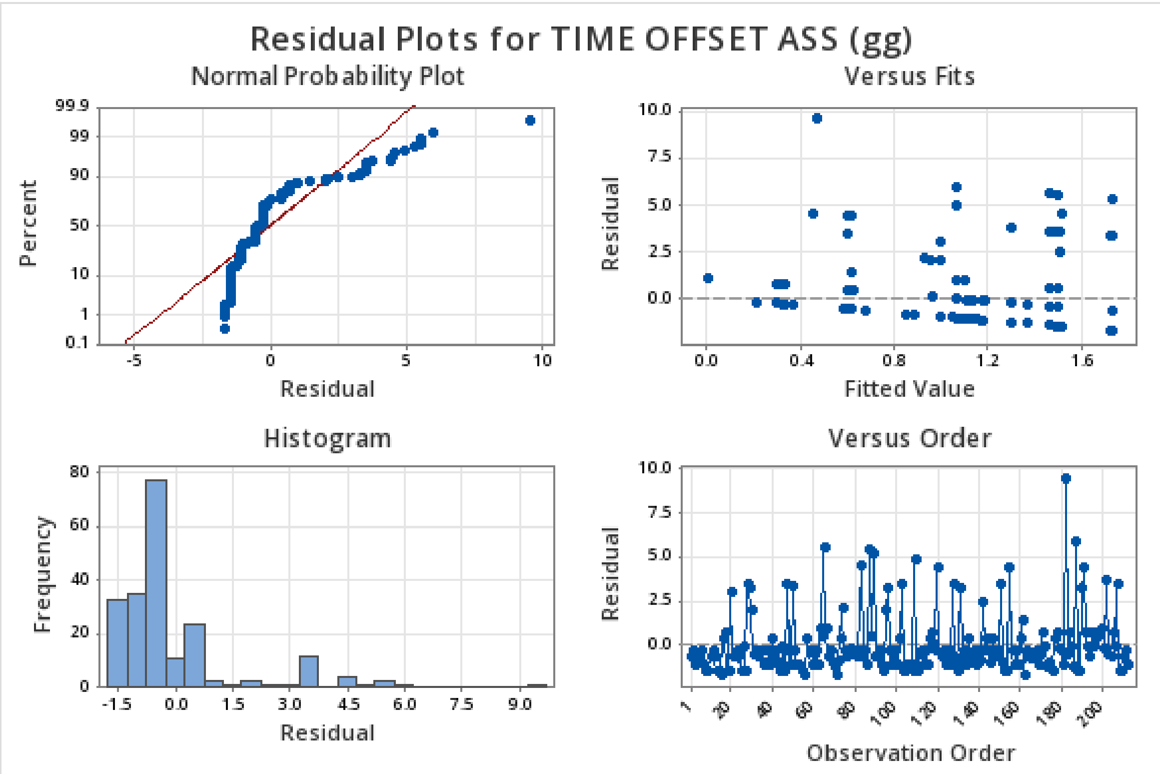

Figure 13: Residual plot graphs – Smallware category

The residual plot graphs overall look good, but it's clear that the assumption of normality is not entirely met because the points do not align with the straight line. Despite this, the model can still be considered valid overall.

Now, let's examine the coefficient table to confirm if the expectations that held true in the case of the "electronics" product category are also valid in this model.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.976	0.191	5.10	0.000	
DISTANCE (km)	0.00753	0.00238	3.16	0.002	219.54
PRICE U (€)	-0.871	0.270	-3.22	0.001	224.48
QUANTITY RECEIVED	0.000010	0.000062	0.16	0.872	1.37
QUANTITY DISCREPANCY ASS	-0.00014	0.000137	-1.03	0.306	1.04

Table 13: Coefficients table – Smallware category

Also in this case the relationship between the only two statistically significant variables “price” and “distance” are the expected sign, however they display a VIF value that is higher than any possible acceptable value, indicating that the model could have a problem.

The issue of the analysis for the product category "smallware" could derive from the limited variability in the distance between the suppliers, the majority of whom are Italian. It is evident that for a low-cost product like smallware, the company opts for nearby suppliers to minimize delivery expenses and potential delivery disruptions. The absence of variability is also highlighted by the almost total lack of outliers. This underscores the remarkable similarity of the considered variables distance, price, quantity received, and the discrepancy between requested and received quantity

This lack of variability means that the model is not able to detect a significant effect of time offset on price, distance and quantity.

The above hypothesis is confirmed by the fact that, as regards the product category "electronics", the greater variability between suppliers and the fact that they belong to different geographical areas, allowed the model to confirm the effect of the dependent variable.

Model Summary

Metric	Value

S	1.7494
R-sq	6.74%
R-sq(adj)	4.94%
R-sq(pred)	2.88%

Table 14: Model summary – Smallware category

To support the above argument, it can be observed that the values of R-sq, R-sq(adj) and R-sq(pred) clearly indicate that the regression model is not able to explain the variability of the time offset effectively. These results suggest that the model has very limited explanatory power for this product category.

The main reason for these results can be attributed to the low variability in data in this category. In this case it becomes difficult for the regression model to identify statistically relevant relationships between independent variables and dependent ones.

In conclusion, the values obtained for this product category indicate that the model fails to capture time offset dynamics significantly. The low variability of the data makes the model unable to explain the phenomenon effectively and provide reliable forecasts. This may indicate the need to consider other variables more relevant for this category or to take a different approach to modeling data.

4.3 ANOVA

The analysis of variance (ANOVA) presented is intended to determine whether there is a significant difference in delays of suppliers, measured in terms of "time offset", in relation to the product category.

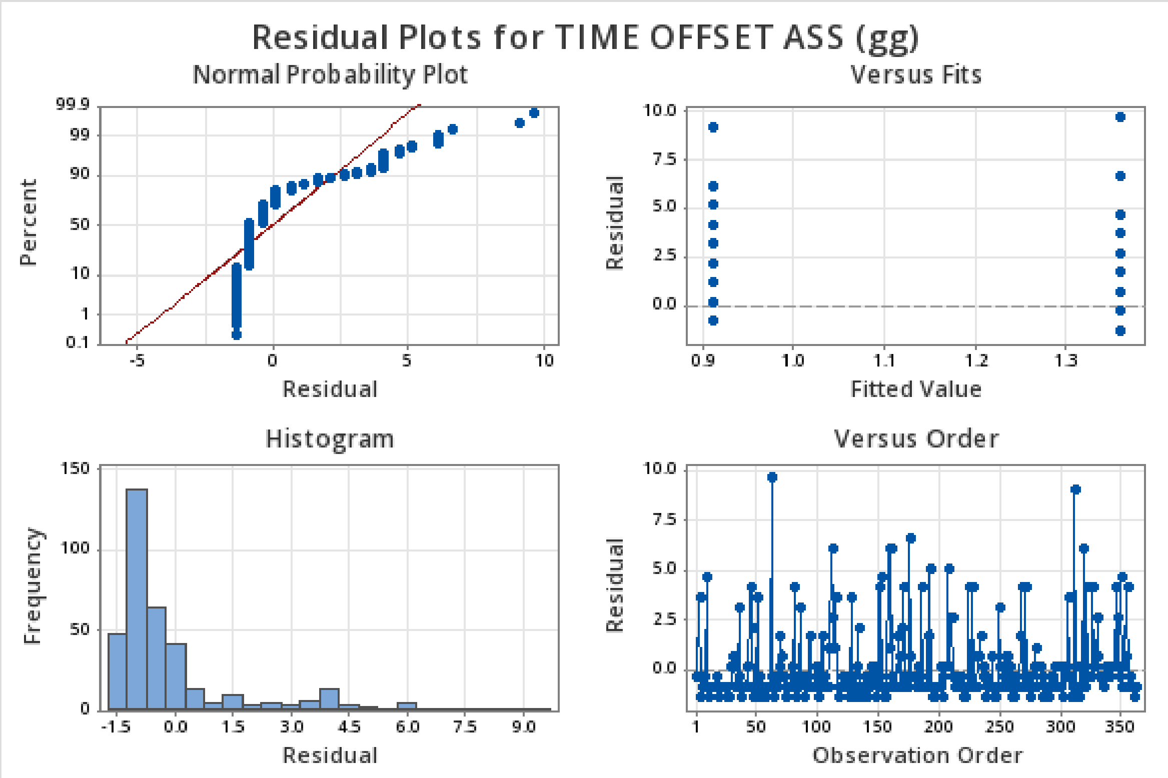

Figure 14: Residual plot graphs – ANOVA analysis

Analysis of residual plot graphs:

- Normal probability plot: the graph shows a deviation from linearity, indicating that the residuals do not follow a perfect normal distribution. This may suggest a possible violation of the normal distribution assumption.
- Residuals vs fit: the distribution in the chart is affected by the fact that there are only two categories. The adjusted values concentrate on two distinct points, corresponding to the averages of the categories. This causes a vertical residue accumulation above the two adjusted values. This distribution is typical when variables with few discrete categories are analyzed.
- Histogram: the graph shows an asymmetric distribution, with a majority of residual concentrated around zero and a long tail towards positive values. This suggests that there could be the absence of linearity.
- Residuals vs order: the graph shows a random distribution, with no obvious pattern over time. This indicates that there is no obvious correlation between the residuals and the order of observations, suggesting that there is no autocorrelation in the residues.

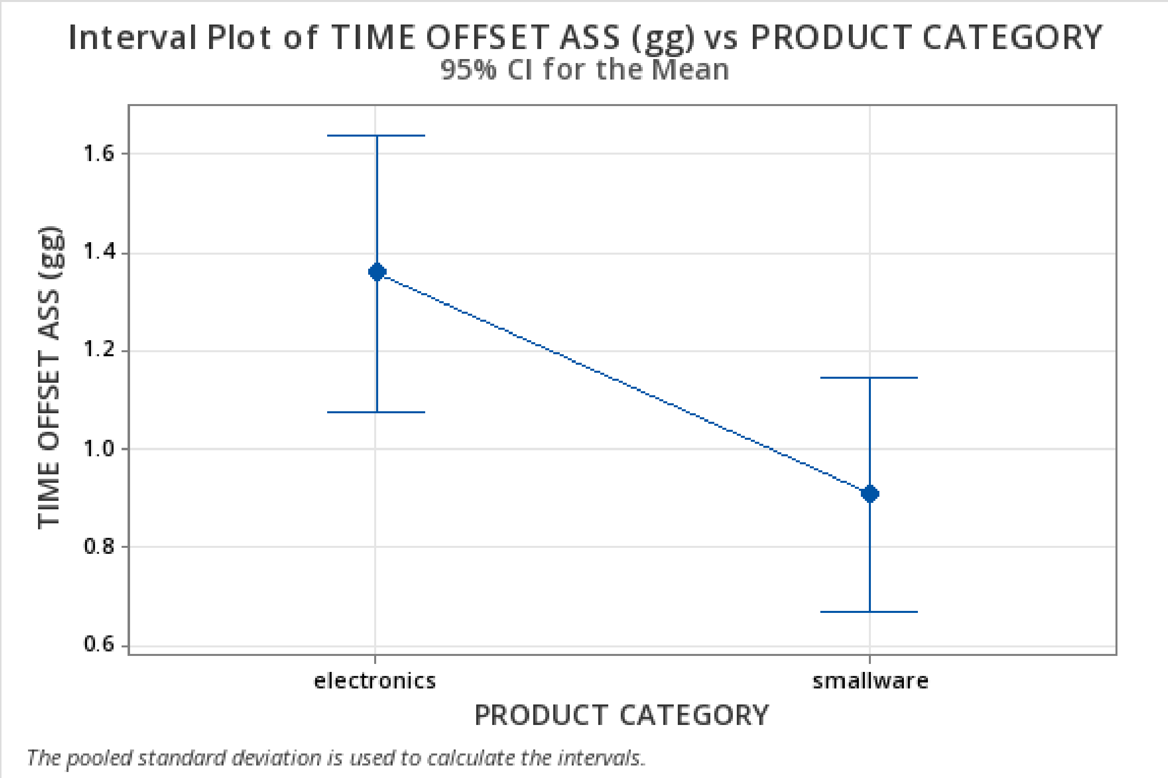

Figure 15: Interval plot graph – ANOVA analysis

The confidence interval graph represents the estimated range in which the true average value of delay falls for each product category with a 95% confidence. The vertical lines show the ranges for each category, and the central point represents the estimated average. The confidence interval for electronics is higher, indicating a longer delay than smallware. Since the ranges do not overlap, we can conclude with 95% confidence that there is a significant difference between the two groups.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
PRODUCT CATEGORY	1	17.76	17.759	5.70	0.017
Error	360	1121.86	3.116		
Total	361	1139.62			

Table 15: Analysis of Variance - ANOVA

The f-value of 5.70 in the ANOVA indicates a significant difference between the two product categories. An f-value greater than 1 implies that the differences between groups may not be due to chance. The p-value of 0.017, lower than the significance threshold of 0.05, confirms that the difference observed is statistically significant, with only 1.7% probability that it is due to chance. Therefore, it can be concluded that there is a significant difference between the two product types.

Model Summary

Metric	**Value**
S	1.7653
R-sq	1.56%
R-sq(adj)	1.28%
R-sq(pred)	0.47%

Table 16: Model summary – ANOVA analysis

The value of S represents the dispersion of residues around the regression line, indicating the extent of the gap between the observed values and those predicted by the model. In this case S is 1.76530, suggesting that on average the delays of suppliers deviate by about 1.77 units from the estimated values. A high value of S denotes low model accuracy with significant residue. This is consistent with the low value of R-sq, which indicates that the "product category" variable explains only a small fraction of the overall variability of delays. As a result, although the ANOVA shows significant differences between product categories, the model has high inaccuracy in individual delay predictions.

5. How lead time negatively impacts on the operational efficiency of a company: company at issue

5.1 Introduction

The main purpose of this research is to explain the difficulty of the management of long and complex supply chains, which contain a lot of suppliers far away from the leading company. Globalization has improved many aspects, first of all the access to a large variety of suppliers and so also technologies, but, at the same time, a lot of problems related to the complicated management of demand timing and variability, especially in the presence of providers with extended lead times.

In the specific case, when a supplier presents very long lead times, for example many weeks between production and transport time, procurement of components becomes crucial and is complicated by the necessity to base every decision on long-term demand forecasts. This type of planning can expose the company to significant risks, in particular the ones which have a business base on just in time production. This can be due to the fact that market conditions and the needs of the client can change drastically during the supply of the material. These variations can lead to situations in which some planned stocks, destined to cover a demand of months, are sufficient to cover a much smaller demand, even lasting for more than a year.

Particularly this situation may be possible when, during the lead time of the supplier, the customer demand is characterized by a drastic cut of production. In this case, the stock quantity becomes excessive with respect to the new needs, and this can lead to problems in the supply chain and inventory management. The unpredictability of demand has become even more evident in recent years, as the automotive industry has faced extraordinary global events such as the pandemic, production shutdowns and disruptions to the international supply chain. It has become fundamental for companies, especially the ones with a complex supply chain, to improve accuracy of demand forecasts.

Here is a real case study which explains in a practical way the topic above analyzed. In this analysis is considered a supplier located in China, characterized by a production lead time of 4 weeks and a transport lead time of 7 weeks which makes careful planning of the quantity of material to be ordered crucial in order to avoid the risk of overstock, but at the same time exposes the company to problems related to drastic cuts in demand by the customer. The situation which has occurred in this case.

5.2 Table content

In this particular case, the client needs four different types of final products, each of which requires specific components from the Chinese supplier for production. Specifically, the supplier provides two types of components to the company, each of which is utilized in the assembly of two different final products. This is further explained in the table below:

TABLE 1	**C1**	**C2**
FP1	1	
FP2		1
FP3	1	
FP4		1

Table 17: Component requirements on the final product

This scheme explains how the component one is assembled in the final product one and two, and the second component is assembled in the final product three and four.

	Final products demand						
Product type	**04/2023**	**05/2023**	**06/2023**	**07/2023**	**08/2023**	**09/2023**	**10/2023**
FP1	Demand of each final product per month						
FP2							
FP3							
FP4							

Table 18: Demand for final products

		Components and final products stock stock							
Stock	**Product type**	**stock**	**04/2023**	**05/2023**	**06/2023**	**07/2023**	**08/2023**	**09/2023**	**10/2023**
379	**FP1**	Actual demand of pieces by eliminating stock =							
84	**FP2**								

0	**FP3**	Demand of FP - stock FP
0	**FP4**	
8889	**C1**	Remaining stock of each component for month =
3384	**C2**	Stock at the start of the month - Demand of the associated FP

Table 19: Final stock of components considering the final products' demand

The first table shows the forecasted demand for the next seven months. The second table displays the current stock of final products, and the remaining stock of components associated with the demand for the final products, which together form the company's inventory being analyzed.

5.3 Analysis

18/04/2023 SITUATION

On the 18/04/2023 the demand forecast send by the customer was the following one:

	Final products demand						
Prod type	**04/2023**	**05/2023**	**06/2023**	**07/2023**	**08/2023**	**09/2023**	**10/2023**
FP1	2394	3087	1029	1575	2373	2100	693
FP2	63	189	63	147	399	588	189
FP3	0	0	0	0	0	588	105
FP4	0	21	42	147	714	861	147

Table 20: Demand for final products in April 2023

A delivery of 2880 units of both components was expected in June 2023. Based on the forecast, the new requirement for components one and two is needed in November 2023.

As a consequence, an order for 4680 units of both components and 1080 units of component two was placed to be delivered in October 2023.

		Components and final products stock stock							
Prod type	**stock**	**04/2023**	**05/2023**	**06/2023**	**07/2023**	**08/2023**	**09/2023**	**10/2023**	**11/2023**

FP1	231	2163	3087	1029	1575	2373	2100	693	1549
FP2	0	63	189	63	147	399	588	189	387
FP3	0	0	0	0	0	0	588	105	387
FP4	0	0	21	42	147	714	861	147	258
C1	12263	10100	7013	8864	7289	4916	2228	1430	-506
C2	1257	1194	984	3759	3465	2352	903	567	-78

Table 21: Stock of components in April 2023

12/09/2023 SITUATION

Below the forecast of the customer's demand in September 2023. Comparing this table with the one that represents the forecast in April 2023 it is possible to see that the customer had already started to cut the requests.

	Final products demand							
Prod type	**09/2023**	**10/2023**	**11/2023**	**12/2023**	**01/2024**	**02/2024**	**03/2024**	**04/2024**
FP1	0	966	1260	1428	1806	4200	2961	3297
FP2	0	378	945	231	1281	1386	441	399
FP3	0	0	0	0	0	0	0	0
FP4	0	0	294	357	378	546	840	42

Table 22: Demand for final products in September 2023

Taking into account the company's inventory, the total availability of components should have been enough to meet the demand until January and February 2024.

		Components and final products stock stock						
Prod type	**Stock**	**09/2023**	**10/2023**	**11/2023**	**12/2023**	**01/2024**	**02/2024**	**03/2024**
FP1	379	0	587	1260	1428	1806	4200	2961
FP2	84	0	294	945	231	1281	1386	441
FP3	0	0	0	0	0	0	0	0
FP4	0	0	0	294	357	378	546	840

C1	8889	8889	8302	7042	5614	3808	-392	-3353
C2	3384	3384	3090	1851	1263	-396	-2328	-3609

Table 23: Stock of components in September 2023

25/03/2024 SITUATION

However, during these months the demand from the customer has been subjected to a further cut, which increasingly compromises the company's situation.

	Final products demand							
Prod type	**03/2024**	**04/2024**	**05/2024**	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**
FP1	1260	1050	1617	924	1260	1260	1533	1071
FP2	21	378	693	273	1197	1155	1470	1365
FP3	0	0	0	0	0	0	0	0
FP4	0	0	0	21	105	189	231	21

Table 24: Demand for final products in March 2024

With the delivery of components in October 2023, the stock of the company would have been able to cover the demand until August 2024.

		Components and final products stock stock							
Prod type	**Stock**	**03/2024**	**04/2024**	**05/2024**	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**
FP1	1	1260	1049	1617	924	1260	1260	1533	1071
FP2	126	21	252	693	273	1197	1155	1470	1365
FP3	0	0	0	0	0	0	0	0	0
FP4	0	0	0	0	21	105	189	231	21
C1	3316	6736	5687	4070	3146	1886	626	-907	-1978
C2	2875	3934	3682	2989	2695	1393	49	-1652	-3038

Table 25: Stock of components in March 2024

It is also interesting to analyze how, even without the arrival of the component pieces in October 2023, the company's existing stock would have been able to meet the demand until May 2024 for component one and until August 2024 for component 2. However, in

September 2023, without considering any deliveries, the stock would not have been enough to cover even the month of November 2023.

		Components and final products stock stock							
Prod type	**Stock**	**03/2024**	**04/2024**	**05/2024**	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**
FP1	1	1260	1049	1617	924	1260	1260	1533	1071
FP2	126	21	252	693	273	1197	1155	1470	1365
FP3	0	0	0	0	0	0	0	0	0
FP4	0	0	0	0	21	105	189	231	21
C1	3316	2056	1007	-610	-1534	-2794	-4054	-5587	-6658
C2	2875	2854	2602	1909	1615	313	-1031	-2732	-4118

Table 26: Stock of components in March 2024, without the delivery of components in October 2023

24/06/2024 SITUATION

To further confirming the drastic drop in demand it is possible to make the same comparison of March in the month of June.

	Final products demand							
Prod type	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**	**11/2024**	**12/2024**	**01/2025**
FP1	0	840	1260	1050	1050	1344	1155	1092
FP2	0	441	819	798	504	462	273	441
FP3	0	0	0	0	0	0	0	0
FP4	0	0	63	21	21	42	21	21

Table 27: Demand for final products in June 2024

With the updated request from the customer the stock of the components will be sufficient to cover the demand until the start of 2025, considering the delivery of components in October 2023, while in March the new need for pieces was in August 2024.

		Components and final products stock stock							
Prod type	**Stock**	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**	**11/2024**	**12/2024**	**01/2025**

FP1	5	0	835	1260	1050	1050	1344	1155	1092
FP2	64	0	377	819	798	504	462	273	441
FP3	0	0	0	0	0	0	0	0	0
FP4	0	0	0	63	21	21	42	21	21
C1	6374	6374	5539	4279	3229	2179	835	-320	-1412
C2	3409	3409	3032	2150	1331	806	302	8	-454

Table 28: Stock of components in June 2024

It is particularly impressive to analyze how, even without the delivery of October 2023, the stock present in May 2023 should have been able to cover all the demand from the client until August 2024. Further confirming that the was a drop in demand also between March and June 2024.

		Components and final products stock stock							
Prod type	**Stock**	**06/2024**	**07/2024**	**08/2024**	**09/2024**	**10/2024**	**11/2024**	**12/2024**	**01/2025**
FP1	5	0	835	1260	1050	1050	1344	1155	1092
FP2	64	0	377	819	798	504	462	273	441
FP3	0	0	0	0	0	0	0	0	0
FP4	0	0	0	63	21	21	42	21	21
C1	1694	1694	859	-401	-1451	-2501	-3845	-5000	-6092
C2	2329	2329	1952	1070	251	-274	-778	-1072	-1534

34 5g6hejur4iTable 29: Stock of components in June 2024, without the delivery of components in October 2023

5.4 Final cosiderations

Due to this situation the company is currently facing a critical challenge in managing its Just In Time (JIT) production strategy, which relies on maintaining low stock levels to minimize costs and reduce waste. The JIT, as explained above, is designed to ensure that materials arrive exactly when they are needed for production, avoiding the build-up of excess stocks and improving efficiency. However, this strategy becomes increasingly difficult to sustain when dealing with long lead times from suppliers, usually those abroad. The company's long lead times and production lead to orders in larger batches, forcing it to keep more stock than desired.

If the company’s suppliers had shorter lead times this would allow for more frequent and smaller deliveries, which would better align with the need to minimize stocks. This would improve the flexibility and responsiveness of the company, allowing it to adapt orders according to production needs in real time. However, foreign suppliers often introduce complications such as longer shipping times, customs delays and other logistical issues.

This highlights the significant impact of lead time on the company’s supply chain and overall production strategy. Long lead times reduce the company’s ability to remain agile and responsive, often causing increased inventory costs or delays in production.

6. Conclusion

The aim of this thesis was to analyze the impact of supplier lead time on the automotive supply chain. To achieve this, a linear regression model was developed using the Minitab software. Lead time, defined as the time between placing an order and receiving the product or component, is a crucial factor in automotive production management. With the increasing globalization, supply chains have become more intricate and involve suppliers from various parts of the world. Longer lead times, often associated with suppliers farther along the global supply chain, can lead to significant delivery delays. The interconnectedness of markets and the expansion of international supply networks have heightened the vulnerability of supply chains to external risks, such as logistical disruptions or changes in trade regulations. Within the automotive sector, where production operates with strict precision and minimal margins for error, delays or advances in deliveries can jeopardize the entire production cycle, impacting costs, timelines, and company competitiveness. Consequently, globalization has heightened the complexity of lead time management, necessitating more sophisticated planning to uphold high levels of efficiency.

In the automotive industry timely delivery of components is crucial, especially for companies that follow the Just-In-Time practices as in the case of the studied company, to minimize storage costs by synchronizing production with demand. Any differences between expected and actual delivery times can cause disruptions in the assembly line, leading to significant costs due to production halts and emergency management. Therefore, effectively managing lead times is essential for maintaining smooth and efficient operations, impacting not only productivity but also the company's ability to adapt to changes in market demand.

A linear model was constructed to analyze how determinate variables affect the supply chain. So, the model aimed to show how various factors influence lead time and establish a connection between independent and dependent variables. The final goal was to build a linear regression model that could explain lead time variations based on collected data and identify the most influential variables.

In the case of the company being studied, the lead time provided was a fixed value set internally by the company for each supplier. This inflexibility made it impossible to create a model based on lead time as the dependent variable because a fixed value doesn't accurately reflect the actual differences in delivery times. To address this issue, it was decided to use the time offset as the dependent variable. The time offset represents the difference between the expected arrival date and the actual delivery date, allowing for the capture of variability in lead time and providing a more accurate indication of the suppliers' performance by measuring delays or advancements compared to the established date.

The analysis included a comprehensive set of relevant variables, such as distance between supplier and company, unit price of the products, total cost of the order, quantity received, and any discrepancies in the quantity delivered compared to the order. The primary goal was to assess the statistical significance of each variable and understand how it influenced the time offset. To achieve this, various statistical techniques were applied, including significance tests and the construction of linear models. By analyzing these variables, the study sought to uncover which elements had the most substantial impact on the time offset, helping to pinpoint inefficiencies and areas where delays could potentially be reduced. This approach enabled a more precise understanding of how operational changes could lead to tangible improvements in the supply chain's overall performance.

The use of time offset has yielded significant results, enabling the identification of factors affecting delivery delays. For instance, it was discovered that the geographical distance between the supplier and the company is a noteworthy factor, showing a positive correlation. This means that the farther the supplier is, the higher the chance of delays or advancements due to logistical complexities such as longer transit times, transportation disruptions, and external factors such as severe weather conditions. Therefore, distance represents a logistical risk that necessitates careful planning and management.

The unit price of the product was an important factor that affected delivery times. Orders with higher value products were usually delivered more quickly. This is because suppliers tend to provide more precise and timely service for high-value orders. Additionally, companies that receive these orders often choose to invest more to ensure better service levels. By spending more, the company hopes that its suppliers will allocate more resources and attention to these orders, leading to greater precision and punctuality.

To improve the accuracy of the analysis, it was decided to conduct a specific study on each of the two different product categories contained in the database, smallware and electronics, given their diversity. It is actually easy to understand the significant difference between the two types of goods. Smallware items, like screws, are low-cost and typically ordered in large quantities, while electronics, such as electrical circuits, are more expensive and ordered in smaller lots. This difference was also confirmed by the ANOVA analysis.

Confirming what was stated previously, the two analyses yielded completely different results. The category of electronic components, in particular, highlighted how distance was a determining factor for delivery punctuality. Additionally, the received quantity was also significant: large volume orders require longer preparation times, increasing the time offset. Logistics also become more complex for large orders, with delays due to the need to consolidate shipments. In the case of the smallware category, instead, almost all the analyzed variables were not found to be significant. The suppliers in this category exhibited very similar characteristics, limiting the ability to assess the impact of the variables on the time offset. This suggests that other variables, such as production capacity or internal logistic management, may be more relevant in explaining delays.

However, the analysis has highlighted significant difficulties in using linear models to accurately represent the complexity of the automotive supply chain. The low R-sq values observed indicate that only a minimal portion of the variability in time offset is explained by the independent variables included in the model. This suggests that many important factors influencing delivery times are not being captured by the linear framework. Furthermore, the predicted R-sq pred values were also notably low, which highlights the model's inability to generalize well when tested on new or unseen data. This poor predictive performance suggests that the model is not robust enough to handle the dynamic and multifaceted nature of real-world supply chains in the automotive sector. The low R-sq pred, in particular, reveals that the model fails to offer reliable insights for future operations, making it less effective as a tool for decision-making.

The normal probability plot and the histogram graphs have also confirmed slightly deviations from normality assumptions, further highlighting the inadequacy of the model. Furthermore, the residual vs fit and residual vs order plots graphs have shown non-random patterns in some cases, suggesting autocorrelation and a lack of linearity between the variables. Despite the removal of outliers, the results have not improved much, confirming the complexity of the industry. These findings, along with low R-squared values, suggest that linear models are not sufficient to represent the complexity of the automotive supply chain. This complexity is influenced by numerous external variables, such as customs delays, natural disasters, logistical problems, and price fluctuations, which cannot be easily incorporated into a linear model. More advanced and flexible models, capable of handling uncertainties and non-linear dynamics, could provide more accurate results.

Despite these limitations, the analysis has still identified some relevant variables, such as the geographical distance from suppliers, which has shown a significant impact on delivery punctuality. This result confirms that managing suppliers located farther away requires greater planning and control.

In conclusion, the analysis highlights the challenges and complexities in managing the supply chain in the automotive sector, especially regarding the influence of lead time on delivery times. Although the linear model used provided limited results, it still allowed for the identification of statistically significant factors such as geographical distance, unit price of products, and quantity received. However, it is clear that there is a need to adopt more sophisticated models to address the challenges of such a dynamic and interconnected automotive system. Advanced models capable of handling uncertainties and non-linearities could be the key to optimizing processes and improving the operational efficiency of companies.

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