Identifying Main Drivers on Inventory Using Regression Analysis

Abstract

Inventory management is essential for satisfying customer demand and reducing logistics costs. Extensive material portfolios, balancing inventory costs versus customer service levels as well as fluctuating demand are factors that influence inventory level. Inventory management is often considered as inventory reduction; quick reduction activities are carried out without knowing the exact root causes of non-target inventory levels. A sustainable and comprehensive approach could be to consider those factors that have a strong impact on inventory to use this information for further inventory optimization activities. This paper therefore gives an answer to the question, how to systematically identify main drivers on inventory using multiple linear regression analysis and how to quantify their impact considering company-specific data and structures. The described approach is applied in a case study at a company in the commercial vehicle industry. Data sets from different locations are analyzed and compared. It will be shown in a methodical way that few factors have a strong linear influence on inventory level and differ depending on the characteristics of the respective location. Companies can thereby analyze main drivers on inventories e.g. per location, region, sales channel or company-wide, depending on the chosen data set. The results can be used to identify root-causes for non-target inventory levels and form the basis for company-specific inventory optimization activities.

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1. Introduction

Inventory management is a large research field with high practical relevance. It includes many functions, such as demand planning, inventory controlling and inventory planning. It determines all decision-related facts that have an influence on inventory level (Pfohl, 2000). Inventory optimization refers to the reduction of stock in warehouses, production and the entire supply chain while ensuring high material availability (ten Hompel and Weidenblut, 2011). Furthermore, it is a cross-sectional function that optimizes inventory and material flow within all functional areas. Inventory management also includes integration and coordination functions, since upstream and downstream processes are coordinated (Stadtler, 2002). Many approaches describe how to calculate inventory levels, with the aim of meeting customer demand with minimal inventory costs and stock out costs, also called inventory trade-off. In order to achieve defined inventory strategies, targets and handling this trade-off, it is important to understand pre-defined parameters and factors which influence stock level.

Many approaches addressing how to identify main drivers on inventory exist in literature. Also qualitative factors and parameters are mentioned that affect inventory to a large extent. However, the interaction of all factors and their effect on inventory level has not been analyzed and quantified in an integral approach. In particular, it is possible that parameters which have not been considered for optimization activities have a major impact on inventory. Company specific structures and organizational set-ups might also affect inventory at a certain stage.

In order to proactively avoid non-target inventory levels, it is essential to identify the root causes of the non-target inventory level. These root causes may appear along the entire supply chain and within different departments. Non-target inventory levels might be generated actively through wrong planning decisions, parameter settings and human influences or indirectly through interactions with other parameters. As a result, non-target inventory levels may arise, without knowing which parameter, decision or set-up has the biggest influence on inventory. This problem is neither sufficiently considered by practical approaches nor by theoretical methods.

This paper therefore presents an approach to identify those factors that influence inventory the most and have led to non-target inventory levels in the past. We will present a method to analyze whether categorical and metric factors have the same impact on inventory or how a potential difference may be quantified. In addition, we will examine whether different plant structures and characteristics have an effect on the main drivers on inventory. The approach presented in this paper was undertaken based on real data provided by a company in the commercial vehicle industry. For this purpose, we formulate the following research questions:

1. How can main drivers on inventory be identified in an analytical way?
2. How can main drivers' impact on inventory level be quantified?
3. How can company-specific structures be considered in determining main drivers on inventory?

The remainder of the paper is structured as follows: Section two provides an overview of standard definitions and current approaches to inventory drivers analysis. In section three, we describe how potential influencing factors were collected and classified based on literature research. Section four describes a method for analyzing the collected drivers on inventory using multiple linear regression analysis. The analysis results are outlined in section five. Section six contains an interpretation of the results, and section seven concludes the paper.

2. Literature review

Inventory levels are affected by a large number of factors. These factors may be internal or external and appear along the supply chain. Demeter and Golini (2013) consider this aspect and cluster drivers on inventory in four categories: Market factors, internal operations, supply chain characteristics and business strategy. Cachon and Fisher (2000), Lee, Padmanabhan and Whang (1997) as well as Lee, So and Tang (2000) described information sharing within and between companies as vital for efficient inventory management. However, they also analyze that external information sharing using computer-based technologies such as collaborative planning and forecasting or vendor-managed inventory can reduce supply chain costs up to 35%. Information flow between actors within the supply chain has been identified as a driver on inventory: Van Ackere, Larsen and Morecroft (1993) run a simulation study to quantify this impact.

Companies also pushing inventory holding responsibilities to suppliers in order to reduce capital lockup and own holding costs (Fazel, 1997). The impact of outsourcing of inventory was shown by Kakabadse and Kakabadse (2000): Based on a survey applied by Cranfield School of Management this driver was identified. D'Aveni and Ravenscraft (1994) stated that inventories can be better managed applying internal rather than external communication and coordination. In addition, long lead-times due to long distances lead to higher inventory levels (Golini and Kalchschmidt, 2011; Kouvelis and Gutierrez, 1997). Long distances between customers and suppliers, especially in global supply chains, lead to an increase in inventories to guarantee flexibility and variability (Stratton and Warburton, 2006). Lieberman, Helper and Demeester (1999) analyzed this correlation using standard inventory models as well as empirical studies. Inventory levels also depend on material costs. Beamon (1998) showed that inventory costs increase if material costs exceed other logistics costs. This approach is based on Porters correlation analysis between material costs and market characteristics (e.g. suppliers number and bargaining power) (Porter, 1980). Furthermore, the customer order penetration point, or decoupling point, has a huge impact on inventory levels (Olhager, 2003; Naylor, Naim and Berry, 1999). Naylor, Naim and Berry (1999) differentiated between the different inventory types such as buy-to-order (suppliers stock), make-to-order (raw and semi-finished stock), assemble-to-order (WIP stock), make-to-stock (finished goods stock) and ship-to-stock (customers stock). Depending on the inventory policy, a decoupling point can be set (Naylor, Naim and Berry, 1999). Olhager (2003) explained that WIP stock and risk of obsolete stock can be reduced setting the decoupling point close to the beginning of a supply chain. A forward shifted decoupling point increases WIP stock because of forecast-based materials (Olhager, 2003). Demeter and Matyusz (2011) run an empirical study in the manufacturing industry on the correlation between decoupling points and inventory levels. According to their study, assemble-to-order companies have lower input inventories and WIP inventories compared to make-to-order companies showing higher input inventories and make-to-stock companies with higher finished goods inventories. Moreover, they also showed how the type of production process impacts inventory levels. Companies organized in job-shops show higher WIP stock compared to companies with dedicated lines. Companies with cellular layout show no empirical trend of higher inventories (Demeter and Matyusz, 2011).

Literature review shows that inventory levels may be affected by a large number of factors, such as communication, production processes, lot sizes. Those factors are included and combined in the aforementioned approaches, may correlate with each other, and are in different causal loops with respect to inventory management. They do not have the same level of impact on inventory. The impact may be linear and/or non-linear. Production leveling activities potentially explain inventory levels at a higher stage than purchasing volumes. The level of impact plays an important role in terms of inventory optimization: The higher a factor's impact on inventory, the greater the opportunity to control inventory by adjusting the factor under consideration of its interaction with other parameters. Depending on the factors considered in the supply chain, the factor-specific impact on inventory may vary. This leads to the following hypothesis:

Factors influence inventory level with a different intensity and in an either direct or indirect way.

Therefore, a more efficient way to control inventory could be to preventively avoid high inventory levels by optimizing the main drivers with regard to their correlation with other material planning parameters. There are many opinions and approaches with respect to which factors influence inventory the most, however, an analytical analysis is missing considering the described approaches without a pre-selection. Analyzing all potential drivers on inventory in an analytical way allows an objective identification of the main drivers. Adjusting factors showing a heavy linear impact should also affect the amount of inventory and lead to smaller differences between actual and target inventory levels. These drivers may differ between companies and industrial sectors. It is therefore essential to identify the influencing factors on inventory on a company-specific basis and optimize them continuously. This allows a proactive inventory control and management. The identified main drivers on inventory can accordingly be used as variables within optimization models.

In order to substantiate this research gap, an analytical procedure will be developed in the following.

3. Collection and classification of potential drivers on inventory

Many potential factors influencing inventory were collected through literature research. The identified factors can be found on different levels within a company and are connected to different processes. Since each factor's influence should be connected to the causal part within the supply chain, a factor structuring according to the various parts of the supply chain was chosen. The SCOR model is one way to structure the factors. SCOR aims to analyze and configure supply chain processes according to the following supply chain segments: Source (S), Make (M), Deliver (D) and Plan (P). A structuring based on SCOR allows the factors to be allocated to the segment in the supply chain where they appear. They affect inventory in both the short and long run. Some factors can easily be quantified, others are human or strategic factors, such as communication and coordination, that can hardly be quantified. In order to better derive actions for improvement regarding inventory management, the identified factors were classified. Such a classification allows differentiation, among others between quantifiable and non-quantifiable factors. Factors can be divided into categorical or metric scales (see Table 1). To quantify the influence of factors with the greatest effect on inventory, metric data is needed in order to apply arithmetical operations.

Table 1: Excerpt of factor structuring based on SCOR

Factor	S	M	D	P	Categorical	Metrical
Order quantity	x					x
Deliveries from suppliers	x					x
Product mix				x		x
Prime material		x				x
Delivery qty. to customer			x			x
Deliveries to customer			x			x
Delivery per-formance	x	x				x

In total, 111 internal and external factors, split into 58 metric and 53 categorical factors, were gathered.

Now, the question is how to identify the main drivers on inventory. There are many methods for analyzing the predominant influencing factors. To identify the main drivers on inventory, we use multiple linear regression analysis. Compared to other methods, it is a clear mathematical approach to objectively describe the dependency between one target variable and one or several independent variables based on empirical data. All of the collected factors can be combined with each other in order to determine the strongest influence on inventory. Moreover, categorical factors can also be analyzed using this mathematical method. Using this approach, qualitative factors such as communication, standards or processes collected during the literature research can also be included in the analysis as a coded variable. As a last step, all identified main drivers on inventory must not correlate with each other, so a correlation matrix needs to be analyzed.

4. Data based analysis using multiple linear regression analysis

Multiple linear regression analysis is often deployed as part of general regression analysis. Multiple indicates that more than one describing variable is analyzed, linear means that the focus is on linear relationships between the describing variables and the target variable.

In this case, the target variable is inventory, the describing variables are all of the aforementioned 111 collected factors. For these 111 factors, the multiple linear regression analysis is applied in order to identify the combination of factors having the strongest influence on inventory.

The theoretical test run was as follows:

- Describing factors: 111 collected factors (e.g. minimum order quantity, lot size, communication, etc. with either semi-annual mean values, cumulated absolute values or binary-coded variables)
- Target value: Inventory level

- Scope of study: 6 months arithmetic mean of describing factors
- Dimension of area of study: Quantity of collected describing factors
- Test run: Linear, logarithmic and squared model

The describing values refer to the collected factors. The area of study contains the average values of all describing factors to explain the target value that is the inventory level. The dimension of the scope of the study is defined through all collected factors whose impact on the target value shall be identified. A linear model is chosen in order to identify the target values' linear dependency on the describing factors. A linear model reveals the direct impact on the expected target value if describing values are changed.

To identify the impact of variables that influence inventory, five statistical key figures with the following ranges are used (for a detailed description of the below mentioned key figures please refer to Backhaus et al. (2011), Hatzinger, Hornig and Nagel (2011) and to Crawley (2007)):

- the adjusted R squared (R^2) with adj. $R^2 \geq 0.7$,
- the F-test and/or p-value with $p < 0.001$,
- the normal probability plot (Q-Q plots),
- the AIC (An Information Criterion), with the AIC as small as possible, and
- the variance inflation factor (VIF), with VIF close to 1 .

Real data from a company in the commercial vehicle industry was used for the regression analysis and to accomplish the described test runs. Materials (e.g. their inventory levels) and factors (e.g. their levels per material) from three different production locations of the commercial vehicle company in the USA, France and the Czech Republic were analyzed. Each location has a different characteristic within the supply chain. Table 2 shows the attributes and location specifications:

Table 2: Plant characteristics

	USA	Czech Republic	France
Product portfolio (number of variants)	High	Middle	Low
Sales channels	OE, OES, ICO, IAM, Reman	OE, OES, ICO, IAM	ICO
Location structure	Production, Distribution	Production	Production
Manufacturing penetration	High	Low	Medium
Inventory space (x) [m²]	x > 10,000	2000 < x ≤ 10,000	1,000 < x ≤ 2,000
Analyzed part numbers	18,017	4,846	8,137

In Table 2, the abbreviations get the following definitions: OE thereby describes Original Equipment Manufacturer, OES represents Original Equipment Manufacturer Service, ICO refers to Intercompany, IAM is the abbreviation for Independent Aftermarket and Reman represents Remanufacturing.

Analyzing different locations with different characteristics allows us to obtain a more complete picture of potential drivers on inventory and to check whether influencing factors vary depending on the location. In total, data was collected for 31,000 materials.

The analyzed material types were finished goods, semi-finished goods, raw materials and spare parts. For each factor, data was taken from an enterprise resource planning (ERP) system as well as from a product lifecycle management database (PLM database) on a part number level. Due to data availability issues and data quality, values for only 46 metric factors (e.g. safety stock, lead time, throughput time, etc.) and 10 categorical factors (standards, structures, organizational impacts, etc.) for all 31,000 materials were collected. For this reason, not all 111 factors and their combinations could be modeled using regression analysis.

Before modeling all factors, it is helpful to plot the data in a scatter plot. A linear trend of the data might indicate a linear dependency between the dependent and describing variables. If no linear trend is visible, it is possible to transform the variables. In our models, we used linear, logarithmic and squared transformation. Fig. 2 shows two plots of the linear dependency. Each dot represents one material – the y-axis represents the dependent variable (average inventory) and the x-axis represents the describing variable (in this example, order size). The two plots can be described as follows: The optimal linear dependency (left plot) and the real data based plot (covariable order quantity), but logarithmically plotted (right plot).

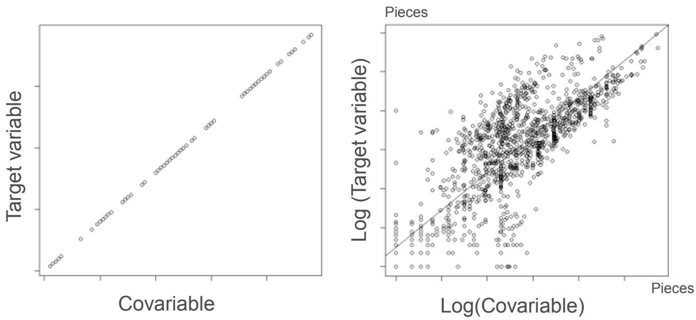

Figure 1: Optimal and transformed data plot showing linear trend

Transforming the data set, in this case using the logarithm transformation, provides the opportunity to summarize the data set and analyze trends.

The influence of only one factor on inventory was analyzed, as was the influence of combinations of factors. In order to include all factors in the model, the forward selection technique was applied: Variables are included sequentially in the regression model if they lead to an increase of the expected target value. In a first step, only two factors were combined with each other, followed by the combination of three factors, four factors, etc. Altogether nearly one billion test runs were analyzed in order to determine the factor combination with the greatest influence on inventory with regard to different model transformations (lin, log, sqrt). The aforementioned test runs yield to the following regression models:

Linear

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{1}$$

Logarithmic

$$\mathrm{Log}(\hat{Y}) = \alpha + \beta_1 \log(X_1) + \beta_2 \log(X_2) + \cdots + \beta_k \log(X_k) \tag{2}$$

and root

$$\mathrm{Sqrt}(\hat{Y}) = \alpha + \beta_1 \,\mathrm{sqrt}(X_1) + \beta_2 \,\mathrm{sqrt}(X_2) + \cdots + \beta_k \,\mathrm{sqrt}(X_k) \tag{3}$$

with

$$\hat{\hat{Y}} \ldots expected\ values\ of\ Y$$

$$\alpha, \beta_1, \ldots, \beta_k \ldots\ Regression\ Coefficient$$

$$X_1, \ldots X_k \ldots Covariables$$

$$1 \ \leq k \ \leq 56$$

Each data set yields one linear, logarithmic and root regression equation and provides a mathematical expectation for the inventory level $\hat{Y}$.

5. Results

The combination of multiple factors considering different data transformation can be seen in Table 5: Depending on the factor combination, the inventory's linear dependency varies. This excerpt only shows those models having an adjusted R^2 higher than 0.9, a p-value smaller than 0.001, also all other aforementioned statistical key figures are fulfilled. No concrete threshold values are defined for adjusted R^2 values in the literature. According to Groß (2010) guidelines, an adjusted R^2 of greater than 0.7 can be interpreted as relatively high, whereby an adjusted R^2 value of less than 0.3 is considered less suitable. An adjusted R^2 between 0.3 and 0.7 describes a linear connection between the depending and describing variable, however, according to Groß (2010), more describing should be added in order to analyze changes in the linear connection.

The “x” in a row indicates those factors whose combination has a high linear influence on inventory. This linear influence is indicated through the statistical criteria described above. Each row stands for one regression equation that describes a strong linear dependency between the marked factors (“x” $\triangleq X_k$) and inventory (inventory $\triangleq$ Y). It is evident that some factors appear in more regression equations than others. As all combinations listed in Figure 2 describe a high linear influence on inventory, the main drivers can be indicated as those appearing in many regression equations with more than 10 x’s per column. This implies that the identified main drivers do not have one bijective beta factor, as they appear in different regression equations. The regression equations for the first and fourth row are as follows:

$$\hat{Y} = -65.7 + 2.5X_1 + 38.3X_2 + 3.2X_3 \qquad (4)$$

$$\hat{Y} = -0.92 + 2.5X_1 + 38.5X_2 - 0.2X_3 + 3.2\,X_4 \qquad (5)$$

with

$$X_1 \ldots Procurred\ Quantity$$

$$X_2 \ldots Product\ Variety$$

$$X_3 \ldots Preferred\ Material$$

$$X_4 \ldots deliveries\ from\ supplier$$

Figure 2 does only show an excerpt of 10 factors analyzed applying a linear model.

Factors combined	**Observations**	**Adjusted R^2**	**p-value**	Safety stock	Procurred qty	Min Order qty	Backlog	Deliveries from supplier	Delivery qty	Delivered qty customer	Amount Customer	Product variaty	Preferred material	...
				0	13	0	5	11	12	9	15	20	17	0
	7175	0.992	2,18E-25		x							x	x	
3	5229	0.992	4,35E-21		x			x				x		
	5163	0.992	1,73E-75		x			x					x	
	5163	0.992	7,43E-21		x			x				x	x	
4	4332	0.993	7,82E-22		x							x	x	
	3310	0.999	3,10E-143		x			x				x		
	3300	0.999	7,53E-191		x			x				x	x	
5	3089	0.994	3,38E-195		x			x				x	x	
	2286	0.812	8,88E-08					x	x		x		x	
	2104	0.999	8,88E-08		x			x				x	x	
6	1483	0.874	4,08E-82		x			x			x	x		
	1483	0.881	1,59E-204		x			x			x		x	
	1465	0.883	6,14E-110		x				x		x	x	x	
7	1465	0.882	1,24E-124					x	x		x	x	x	
	1402	0.886	6,65E-117						x	x	x	x	x	
	1246	0.881	6,27E-203		x				x		x	x	x	
8	1207	0.885	1,31E-85						x	x	x	x	x	
	1160	0.880	4,59E-53						x	x	x	x	x	
	1066	0.832	6,47E-78				x		x	x	x	x	x	
9	1036	0.902	3,47E-46				x		x	x	x	x		
	1036	0.902	4,47E-168				x		x	x	x	x		
	522	0.857	5,21E-03						x	x	x		x	
10	505	0.890	8,38E-61				x		x	x	x	x		
	375	0.895	2,20E-202				x			x	x	x		

Figure 2: Excerpt of regression results per factors combination

Furthermore, four graphical plots were analyzed whether they fulfilled the requirements to consider the respective factor as main driver on inventory. Figure 3 shows the plots representing the example of the factor batch.

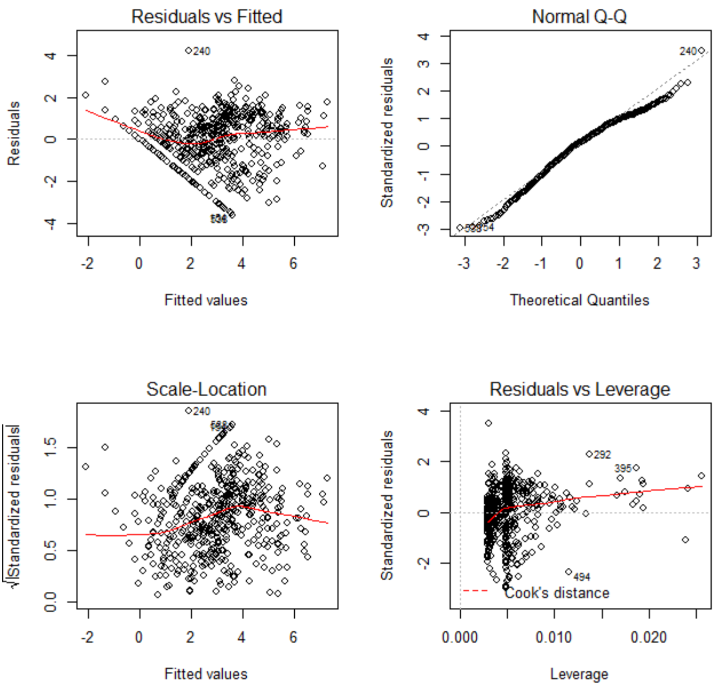

Figure 3: Excerpt of four graphical plots for driver batch

The picture on the top left plots the residuals versus the fitted values. If the residuals' spread (solid line) differs significantly from the dotted line, the linear relation will not be explained sufficiently. The top right picture shows the residuals normal distribution: This is a precondition for applying linear regression, otherwise F-test will not be valid. Significant discrepancies between the normal distribution (dotted line) and the data points show an unreliable model. The third plot at the bottom left uses the same data as the first plot to analyze the scale location. Crawley (2007, pp.402) states: „If there was a problem, such as the variance increasing with the mean, then the points would be distributed inside a triangular shape, with the scatter of the residuals increasing as the fitted values increase.“ The fourth plot at the bottom right reveals the influence of data points. If one data point lays outside the so called Cook's Distance, a strong impact on the model can be interpreted (Groß, 2010). If those data points are taken out of the model, a different linear model might result.

The regression analysis was applied to each location data set as well as to the whole data set (USA plant + France plant + Czech plant). Table 3 shows the main drivers per data set:

Table 3: Main drivers on inventory per different data set

Czech Republic	France	USA	All Locations
Order quantity from supplier	Order quantity from supplier	Order quantity from supplier	Order quantity from supplier
Replenishment time	Batch	Product portfolio	Product portfolio

Czech Republic	France	USA	All Locations
Number of suppliers' shipments	Customer delivery performance	Number of prime materials	Number of prime materials
Quantity issued to customer	Quantity issued to customer	Quality related stock	Internal delivery performance
	Number of shipments to customer	Number of shipments to customer	Number of shipments to customer
	Customer delivery quantity	Customer delivery quantity	Customer delivery quantity
		Number of suppliers' shipments	

The difference in the number of main drivers on inventory per location is related to the number of x's per column as shown in the excerpt in Figure 2.

This allows a comparison of the plants' specifications with the set-up of an entire network. According to Table 3, the factors showing the greatest linear influence on inventory, taking into consideration the whole data set and structured according to Table 1 into Source, Make, Deliver, Plan, are as follows:

– Order quantity (S): The average order quantity of a material. This factor takes every order of a material into account, and calculates an average based on these individual amounts.

– Product Portfolio (P): Product assortment depth. Describes how many components belong to the same “product family”.

– Number of shipments to customer (D): Total number of customer deliveries. The total number of deliveries of a material to the end customers in a specific time period.

– Customer delivery quantity (D): The average quantity of a component delivered to the customer.

– Internal delivery performance (S, M): This factor calculates the internal delivery performance level, also referred to as “ICO delivery performance”.

– Prime material (M): Proportion of use of products from the same product family. The percentage of usage of a component with regard to materials from the same product family.

6. Interpretation of results

The previously listed research questions were answered: The main drivers on inventory were identified analytically, quantified and company-specific analyzed using multiple linear regression analysis. Furthermore, the analysis supports the aforementioned hypothesis: Only a few factors explain inventory level to a great extent. The identified factors may vary depending on industry, material portfolio, data quality, fixed period, etc. However, multiple linear regression analysis can be used to identify the main drivers on inventory on a company-specific basis and explain their level of influence on inventory through the adjusted R^2, among others.

The six main drivers appear at different stages along the supply chain. Earlier studies focused on optimizing specific inventory related areas within the supply chain, e.g. only procurement parameters, or based their approach on empirical studies without quantifying the drivers' impact on inventory and correlation with other factors. Assigning the main drivers on inventory to Source, Make, Deliver or Plan, the results of this study reveal that inventory management has to consider all parts of the supply chain, since they interact with one another throughout the supply chain without correlating with each other. In addition to other aforementioned literature approaches, also qualitative factors were analyzed using coded variables. They were not identified as main drivers on inventory applying this data set. However, multiple linear regression analysis allows their consideration.

Figure 3 shows further statistical criteria that have to be fulfilled: If the normal distribution of residuals is not given, a factor will automatically be excluded as main driver. However, combining it with other factors may lead to a normal distribution of the residuals and improve the model. It is thereby possible to consider drivers on inventory that might have been deleted because of data issues. All identified main drivers on inventory fulfill the requirements: There are no main drivers lying outside the Cook's Distance, the residuals fit to the expected values and data points are not spread in a triangular form.

Depending on the plant's characteristic, the factors show a different linear influence on inventory. Many identified factors can be explained through these characteristics. The Czech plant, for example, is distinguished by high replenishment times, because suppliers are situated far away from the plant. This also leads to higher order quantities from suppliers in order to guarantee that customer demand is met. The identified main drivers "Order quantity from supplier", "Replenishment time" and "Number of suppliers' shipments" affect inventory at the Czech plant due to the procurement structure. The opposite situation can be found at the French plant: there are long delivery times from the plant to the customers due to long travelling distances. The identified outbound-related main drivers on inventory, such as "Quantity issued to customer", "Number of shipments to customer", "Customer delivery performance" and "Delivered quantity to customer" can thus be attributed to the French plant's distributional network.

The USA plant has a high product portfolio and high focus on product variants, which explains the strong linear influence arising from the "Product portfolio" and "Number of prime materials" factors. Due to the USA plant's geographical location, there are long delivery distances both from suppliers and to customers. The other identified main drivers on inventory therefore also affect the procurement and distribution part of the USA plant's supply chain. Overall, the identified main drivers on inventory on a plant level can be ascribed to the plant's structure, or supply chain set-up. Furthermore, factors that cannot be directly related to this structure or organizational set-up provide transparency about other effects on inventory which might not have been realized in the past. In addition, the regression analysis revealed that main drivers on inventory vary depending on the plant's location and structure and need to be identified separately.

7. Conclusion and further steps

The regression analysis is based on historical data, thus the identified drivers explain inventory level in the past. A more efficient way to plan inventory could be to use these results in order to proactively control the inventory level. These factors relate to inventory in a linear way, their optimization will therefore automatically affect the inventory level. Varying these factors continually reduces the risk of creating a non-target inventory level. An improvement measure within the scope of inventory management depends on the kind of factor and may be a defined standard process or a calculation method. The derivation of actions for reacting to inventory level deviations as well as for preventing such deviations in the future is a next step in completing this systematic approach.

Factors were structured according to their appearance within the supply chain, among other aspects (see Table 2). The findings in this study support this structuring, since the identified main drivers appear at different points along the supply chain. Based on these results, improvement measures can be focused on the relevant department as a clear allocation to the appropriate supply chain part.

In addition, analyzing the data set on a location-wise basis allows identification of the location-specific main drivers on inventory and allows location-specific issues to be taken into account. Furthermore, analyzing all data sets at once provides an overall picture of the main drivers on inventory within the network of a company and helps create a common understanding with regard to where the biggest potentials for inventory optimization measures exist in the supply chain.

One next step is to include the valuation class per material and inventory level in the regression analysis. It shall be shown whether "Source" factors have a stronger impact on raw material inventory level than on e.g. finished goods inventory level.

As market and other external factors change over the time, the main drivers on inventory may vary. One next step is therefore to define a regulatory framework where responsibilities and regularities are described. This would allow an inventory improvement process that considers the actual internal and external situation within the supply chain.

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