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REVERSE BULLWHIP EFFECT IN THE AUTOMOTIVE INDUSTRY: CASE STUDY FROM ROMANIA

Abstract

Purpose: The goal of the paper was to analyze data from a short loop supply chain (supplier – manufacturer – customer), seek the reasons for the presence of the bullwhip effect (or a reverse bullwhip effect) and quantify its intensity within a practical case study from an automotive industry company based in Western Romania.

Methodology: Data for this research were gathered over 27 weeks for the case of the most important 50 supplier-customer pairings of the manufacturing plant. The collected data were then analyzed using Holt-Winters exponential smoothing (level, trend and seasonality) and the methods of descriptive statistics: dispersion (range, variance, and standard deviation) and frequency distribution (count, percent, and frequency).

Results: Our results confirm the existence of both the bullwhip effect (BE) and the reverse bullwhip effect (RBE) within the supply chain of the production site, as there are 54% of cases where order variation between the group of analyzed suppliers and customers is surprisingly greater for the latter, with only 12% of cases being the source of the classic bullwhip effect.

Conclusion: According to our research, both effects are present, with a higher prevalence of the RBE, but the intensity of both effects can be significantly reduced by improving planning schedules, internal performance and logistics metrics, whilst also increasing the integration of suppliers and manufacturers in the upstream and downstream supply chain material and information flows.

Keywords: Demand variation, logistics performance metrics, order fluctuation, supply chain integration

1. Introduction

The economic and social importance of the automotive industry contributes to the fact that the industry is a driver of GDP growth and welfare, providing highly skilled jobs and acquiring other horizontal advantages of the industry (a local network of suppliers, building new and modern infrastructure, competitive salaries). At EU level, the automotive industry alone creates more than 2.5 million jobs (8.5% of EU employment in manufacturing) and is driven by the "big five" carmakers and groups (Volkswagen, BMW, Mercedes, Renault and Stellantis) (Thun & Hoenig, 2011). In Romania, where both Dacia and Ford have manufacturing sites, the economic importance of the automotive industry is especially important: 12% of GDP and 30% of exports (in 2022), an established network of automotive suppliers (more than 500 nationally), and over 230,000 specialized jobs account for 17.5% of the manufacturing industry in Romania.

The present paper was inspired by a consultancy research contract conducted at the manufacturing plant of one of the automotive industry suppliers based in Western Romania. The research contract was carried out throughout an entire semester (27 weeks) with the goal to assess logistics and supply chain management effectiveness in view of multiple demand and supply mismatching issues, leading to high variations and fluctuations and increased shortage and overstock issues. The company is currently facing an increase in volume and will do so until 2025, until the newly started extension process is completed. Until then larger volumes, newly launched projects and increasing capacity requirements have to be managed within a facility already running at full tilt (Lücker et al., 2021). Operational performance is thus under serious pressure (Simchi-Levi et al., 2018) and the team is growing with new interns, mostly graduates or internship students (Nikolicic et al., 2019). A wide range of supplier and customer requirements and dynamic daily logistics issues (urgent customer shipments, production backlog and warehouse overstock, delivery issues) can prove quite demanding (Mircetic et al., 2022) even for an experienced logistics specialist (Simchi-Levi et al., 2015), let alone for an intern with lack of experience in such a dynamic environment or sometimes without even the most basic logistics principles, knowledge or induction (Prajogo & Olhager, 2012).

The dynamism of the sector is also enabled by rapid technological advances (Krstić et al., 2021) and quick adoption of new features, but their implementation is subject to lots of technical, legislative and operational challenges (Boada-Collado et al., 2022). One of these challenges is the bullwhip effect (BE), which has received comprehensive attention in the specialized literature (Wang & Disney, 2016), but due to certain market specifics and more recent supply and demand mismatching issues (Ponte et al., 2020), the reverse bullwhip effect (RBE) is also increasingly present. The reverse bullwhip effect (RBE) generates large variations upstream, as opposed to the classic BE, due to short-term market disruptions (price volatility, material scarcity, increasing delivery lead times) that enable opportunistic behavior from customers who order more than usual (the multiplying effect) and create high fluctuations, which distorts the regular flow of goods. Variations and supply chain issues and challenges become more apparent in global environments, where there is much more complexity (Gruchmann & Neukirchen, 2019), as is the case with the automotive industry (Pastore et al., 2019). The Forrester effect explains the reasons why fluctuations in demand increase within the upstream supply chain links in a higher proportion (as a consequence) than those generated in the downstream supply chain links (as a cause). The solution is integrated and real-time communication (Brito et al., 2020), but only in conjunction with realistic and harmonized internal performance metrics (forecast accuracy, production planning, productivity and output metrics, different stage inventory levels, perfect order deliveries) applied by each short loop supply chain (supplier - manufacturer - customer). Multi-tier supplier-manufacturer relationships and the use of EDI (either as partially or fully integrated software programs) as a means for faster (real-time), more reliable (user access and permissions) and longerterm planning (quarter, semester and/or annual forecasts) are not a guarantee against the bullwhip effect if the reliability of the data in the information exchange is not 100% accurate (Papanagnou, 2022).

The objective of the paper was to analyze, assess and interpret data from the short loop supply chain of the manufacturing company (supplier – manufacturer – customer), determine if the bullwhip effect (BE, or the reverse bullwhip effect, RBE) is present, highlight the reasons and quantify its intensity. The task of the research team was also to provide solutions and improvement proposals at the end of the conducted consultancy contract and had the role to combine a practical view with the academic mindset and produce a comprehensive report within this case study from Western Romania.

2. Materials and methods

The data used in this research paper were gathered, discussed and analyzed over a period of one semester (27 weeks) within the framework of a joint research collaboration in order to obtain a comprehensive overview of the scale of the company's internal logistics activity and its short loop supply chain. The key company members (project, group and team leaders, as well as departmental logistics managers) were also involved in the process and contributed to the accuracy of the data used and the relevance of the results obtained. Actual orders were collected from the company's EDI system on the basis of the initial semester forecast smoothed exponentially with trend and seasonality for the case of 50 different customers and 50 most important suppliers of the manufacturing plant. This paper focuses on the short loop supply chain (supplier - manufacturer - customer) of an automotive industry manufacturing company and orders from 100 of its specific suppliers and customers (50 supplier-customer pairings) for the necessary parts to manufacture the end product at the production site not far from Timisoara, Western Romania. The company did not want to disclose either its identity/location (consent was given for general reference only) or certain parts of research carried out independently (all provided within the full report upon the completion of the research contract) in this paper, therefore some steps, links and conclusions may be subject to limitations for the reader.

Data from customer orders are compared to orders from suppliers in the 27 weeks, ranging from absolute values, variations from the overall average (absolute and relative, positive and negative, minimum and maximum) to the overall variation within the entire period for the two sets of data. In this sense, only the average orders from a selection of 10 customers and 10 suppliers are presented for the aforementioned semester, in units. The average order levels (O_{avg}) and weekly variations (O_{var}) calculated throughout 27 weeks for both customers and suppliers are measured by applying the following formulas:

$$O_{avg} = \frac{\sum_{i=1}^{W} O_{w}}{w},$$

where $O_{_{avg}}$ is the average order level and w is the number of weeks [units], and

$$O_{var} = \frac{Ow}{Oavg},$$

where O_w is the actual order level for a given week [%].

Production planning is based on data from actual customer orders in order to compile more reliable forecasts at the manufacturing company. The forecast levels for each week are based on the customer order estimate and then smoothed exponentially with level, trend and seasonality ($\alpha = 0.3$; $\beta = 0.2$; $\gamma = 0.5$). These specific values were chosen by the planning department based on previous results and their precision. A smoother average was targeted for a longer period (a 52-week forecast horizon) with a slight added weight to more recent data (α), trend does not change significantly, therefore the basic longer-term trend was preferred (β) and the chosen value for the seasonal smoothing coefficient was proven more reliable in previous observations than others (γ).

Consent was given only for the average absolute numbers (in units) and broad unit ranges; all other absolute data were subject to a non-disclosure agreement, therefore mostly relative values (percentages) are used for comparison purposes. Relative variations (both above and below average) are expressed in percentage and summed up for both groups of customers and suppliers. The total variation (in %) is then averaged out for the 27 weeks and the gap between the extremities (the difference between the maximum and the minimum variation) is also calculated to determine the amplitude of the range of values. The gap is then compared to the average variation to determine the existence of an additional metric that may add a further cause for generating (an even more intense) bullwhip effect within the short loop supply chain analyzed. The metric was used in order to partially compensate for a further limitation (non-disclosure of the actual gap, since variations are compared as absolute values and not negative-positive ranging values) and provide a more relevant estimation of the degree of variability. A bullwhip effect is present if the overall variation of orders within the group of suppliers exceeds the variation generated within the group of customers analyzed, with certain partial correlations and limitations being possible since our research data could only be revealed to a limited extent, subject to the agreed clearance obtained from the company's management. A 15% order variation level has been agreed with the company's customers where current pricing conditions apply, and the suppliers follow a broad range of terms and conditions. The company uses state-of-the-art EDI systems, is linked with most of its customers and suppliers, and applies the automotive industry standard Just-in-Time (JIT) system.

The objective of the paper was to see if the bullwhip effect was present and, if so, to quantify the extent to which it is expressed within a (very) short loop supply chain (supplier – manufacturer – customer) case study. A selection of the tables and figures with results is provided in the section containing results, as well as comments and interpretations on the sets of data (10 customers, 10 suppliers, and a comparison between the obtained averages for each group of partners in the company's supply chain), whereas the main outcomes are outlined in the conclusion.

3. Results

The results of the present case study were obtained at a manufacturing company located in Romania, close to the city of Timisoara (in the west of the country), the most dynamic automotive industry region where many suppliers have set up or extended their production facilities. The company produces parts for all major car brands from Europe, Asia and North America, including the two car plants based in Romania (the Dacia factory in Mioveni, close to Bucharest, and the Ford factory in Craiova, in the south of the country), but its main customers (more than two-thirds of total sales) are large European carmakers from Central Europe.

Table 1 presents an overall average of all 100 customers (C_{avg}) and supplier average weekly order ranges (S_{avg}), as well as their categorized proportion [%] used for the purpose of comparison in the next part of the section, where a selection of the main 10 customers and 10 suppliers is highlighted.

Table 1 Average range of weekly orders (parts and/or components) per customer and supplier [units]

100+	1000+	10,000+	100,000+	C _{avg}	100+	1000+	10,000+	100,000+	Savg
15	26	8	1	50	2	22	19	7	50
30%	52%	16%	2%		4%	44%	38%	14%	

Source: Author

Most customers (82%) placed orders for a couple of hundred or thousand parts from the automotive industry company based near Timisoara, and more than half (i.e., 52%) between 1,000 and 9,999 units. As expected, these levels are slightly higher for the suppliers providing the necessary components according to the BOM. Most suppliers (82%) received orders of thousands of units (ranging from 1,000 to 99,999), and some of them also received orders of half a million units weekly, on average. Figures 1, 2 and 3 present supplier-customer pairing variations: the average level of orders over the semester (27 weeks) and the actual fluctuation values for each week throughout the analyzed time span.

Figure 1 Supplier 6 (left) and customer 6 (right) weekly order variations [units]





Figure 1 shows the weekly order variations for supplier 6 (left) and customer 6 (right). The patterns are very different in this pairing as customer 6 has a couple of peaks and troughs, the most important are the 2 peaks towards the end of the 27 weeks, whereas elsewhere it has rather stable cyclical ordering behavior. The order pattern of supplier 6 is typical of a batch system, but only 3 orders are placed in the 27 weeks, which then cover the required materials and components for the next 12 weeks, suggesting most likely a longer lead time and/or a critical component with very high ship-

Source: Author

ping costs. With 3 extreme peaks compared to the average, the order pattern and the overall variation of the supplier is greater than a more balanced customer pattern; therefore this situation is subject to the risk of the BE in the event of a slight increase in the customer's orders at a given moment.



4.500 4 001 3.000 2.500 1.500 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

Source: Author

Figure 2 shows the weekly order variations for supplier 7 and customer 7. Customer 7 has a rather cyclical order pattern, with 3 peaks in weeks 6, 12 and 26, and a slight three-week drop in orders (weeks 14-16), but generally a balanced distribution of orders. This trend is followed closely by the order pattern of supplier 7 that had higher than average orders for a few weeks (weeks 4-6, 9, and week 22), and then mostly added only smaller quantities within the remaining weeks, thus confirming a smoother distribution. Overall, both supplier and customer 7 have a rather stable order pattern with no major visible variation difference and a lower risk of exposure to the BE and/or the RBE.



Figure 3 Supplier 8 (left) and customer 8 (right) weekly order variations [units]

18.000

16.00

14.00

12.000 10.00

6.000

17.020

Source: Author

Figure 3 shows the weekly order variations for supplier (left) and customer 8 (right). Their patterns are very different: customer 8 placed a peak order at the beginning of the semester and then orders were very scarce (close to zero). Supplier 8 had a more stable distribution, with cycles (ups and downs). Some weeks recorded higher than average orders (weeks 5, 21, and 24), while others recorded troughs (weeks 9 and 26), and elsewhere the pattern was relatively stable with order volumes around average levels. With 2 extreme peaks compared to the average, the order pattern and the overall variation of the customer were greater than a more balanced supplier pattern, therefore this situation is subject to the RBE. This may be the case in situations where some materials/components are more difficult to obtain, experience delivery interruptions and are commonly used for products of several customers, therefore will have a more stable demand. It may also occur when there is a huge peak in demand for a certain type of product before it becomes part of serial production, or if the customer is subject to the acquisition of additional references as transshipment towards their own network.

9 13 9 13 9 4 5 6 5 6 6 5 2 2 2 3 3 3 4 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26

Table 2 presents the analyzed data series for the customer order variations, which is then used as a means of comparison for supplier order variations (the latter is shown in Table 3 in order to identify the presence of a possible BE and its intensity in the chosen data range). The average order levels in units of 10 main customers within the time span are shown and an overall average is also calculated, as well as the number of weeks with orders above and below average. In this paper, the actual order levels of each week (O_w) are compared to the average level (O_{avg}) by division and expressed in percentage points [%]. The average order variation (variation

1) for the 27 weeks is calculated for each customer, as well as the lowest (minimum variation, V_{min}) and the highest variation (maximum variation, V_{max}) of the same period. The maximum range (variation 2, the difference between the maximum and the minimum variation) is also expressed in percentage points, whereas the variation gap adds up the average variation (variation 1) and the maximum range (variation 2). The lower the level of variation for average, range and gap, the better the chances for a more balanced and reliable production and delivery schedule for the supply chain short loop partners (supplier – manufacturer – customer).

	Average order level [units]	Above average	Below average	Variation (min) [%]	Variation (max) [%]	Variation 1 (average) [%]	Variation 2 (max-min) [%]	Variation (gap) [%]
C1	1,425	6	21	19	315	89.22	296	385.22
C2	204	12	15	2	569	89.85	567	656.85
C3	67	9	18	13	262	97.51	249	346.51
C4	2,298	9	18	4	627	114.18	623	737.18
C5	1,902	13	14	6	107	36.00	101	137.00
C6	506	10	17	4	114	44.44	110	154.44
C7	1,584	16	11	21	153	52.88	132	184.88
C8	970	3	24	18	1656	176.37	1638	1814.37
C9	536	10	17	1	139	49.44	138	187.44
C10	1,542	13	14	6	115	41.00	109	150.00
Overall average	1,103.4	10.1	16.9	9.4	405.7	79.1	396.3	475.4

Table 2 Overview of analyzed order parameters by semester, per customer

Source: Author

The 10 main customers analyzed place weekly orders, on average, ranging from a couple of hundreds to thousands of units, but they each have very different order patterns and fluctuations. The number of weeks where actual orders are below the average number of orders is greater (62%) than those above average, mainly due to specific market trends and seasonality issues. Within the semester, only customer 7 (see Figure 2) ordered over 27 weeks more times than the other customers. This customer began with average order levels, but then started increasing that quantity by up to 3 times for most of the time span, and then suddenly reduced the orders to very low levels towards the end of those 27 weeks. Compared to the average order level, having units above or below average does not necessarily mean better or worse order management: what is really important is matching demand as smoothly as possible without carrying excessive inventory levels.

The largest range of variation (from a minimum of 18% to a maximum of 1,656% compared to the average) is noticed for customer 8 (see Figure 3). In this case, an excessively large order was placed at the beginning of the analyzed period, leading to several other weeks with no orders, and towards the end of the 27 weeks more balanced volumes were requested before shifting again to 2-3 times the average rate. Customers 2, 3, and 4 also follow

an intense range of variation with similar patterns: very low orders followed by an abrupt increase (3-7 times the average), then again very low order levels for most of the period, before suddenly again demanding a very high volume (2-6 times the average) within the final weeks or even in the last week (customer 2 ordered a quantity 6.68 times greater than its average in the last week of the semester). A similar peak demand at the end of the period is also worth mentioning for customer 1. Customers 9 and 10 have a more cyclical order pattern with peaks of 2-2.5 times their average at the beginning, middle and towards the end of the 27 weeks. Customers 5 and 6 (see Figure 1) have a more balanced order pattern, as their orders are much more stable with only 2 peaks (double the average) in the middle of the time span, whereas elsewhere they rarely exceed a 25% order variation.

The average order variation (variation 1) for the 10 customers is just under 80%, with only half of the customers managing to achieve on average up to 50% of their orders (customers 5, 6, 7, 9, and 10). This is mainly due to more typical demand patterns (balanced, cyclical) in their weekly orders as a result of better forecasting strategies and techniques. In contrast, the other 5 customers have more cha-

otic order patterns and higher fluctuations, which is of course noticeable in their increased variations, which are double or even up to 3-4 times greater than those of the first group of customers.

The average range in variation between the same data sets for the 10 customers is almost 400%, which is 5 times greater than their combined actual average, and customer 5 had the most balanced difference between these parameters (36% variation in average orders compared to a 101% maximum variation range). Customers with lower average order variations also share the lowest maximum ranges (in most cases, 2-6 times) as a result of steadier order patterns and a narrower spread between their extreme variations. This enables the automotive industry company to be more reliable in its production and delivery schedules and significantly reduce the risk of a backlog or a shortage.

Table 3 presents the analyzed data series of supplier order variations generated by the company for the corresponding customers from Table 4. Thus, each supplier number (and associated components) corresponds to the customer number in order for the manufacturing company to make and deliver the finished products as per the BOM.

	Average order level [units]	Above average	Below average	Variation (min) [%]	Variation (max) [%]	Variation 1 (average) [%]	Variation 2 (max-min) [%]	Variation (gap) [%]
S1	159	16	11	1	81	16.67	80	96.67
S2	1,134	9	18	3	434	58.44	431	489.44
S3	4,594	18	9	9	78	15.18	69	84.18
S4	53,904	13	14	1	91	30.41	90	120.41
S5	2,222	6	21	100	350	155.55	250	405.55
S6	624	3	24	100	800	177.77	700	877.77
S7	2,297	10	17	13	118	45.18	105	150.18
S8	13,000	14	13	31	108	55.18	77	132.18
S9	7,823	11	16	2	156	50.18	154	204.18
S10	8,208	9	18	14	234	84.55	220	304.55
Overall average	9,396.5	10.9	16.1	27.4	245	68.91	217.6	286.51

Table 3 Overview of analyzed order parameters by semester, per supplier

Source: Author

The company places weekly orders for materials and components with its 10 associated suppliers, ranging on average from hundreds of units to even more than 50,000 units, with slightly different order patterns and fluctuations. The number of weeks where actual orders are below the average number of orders is greater (59%) than when these are above average in a similar proportion to the customers. Within the semester, only 30% of suppliers received orders more times above their average levels throughout the 27 weeks than the rest of suppliers. These suppliers (suppliers 1, 3, and 8) have relatively stable and balanced order patterns received from the manufacturing company, so their production and delivery schedules are also less issue-prone. Similar to the goal of customers, the main objective of comparing the order level with the average level in the case of suppliers is mainly to provide better forecasting capability, predict order patterns and increase regular on-time, in-full deliveries.

The largest range of variation (from a minimum of 100% to a maximum of 800% compared to the average) is noticed for supplier 6. In this case there is a batch ordering system in place and only 3 large orders are actually placed within the 27 weeks: at the beginning, in the middle and towards the final part of the time span, after that no other orders are placed. This is also the case for supplier 5, but the fact that there are more batch orders has reduced the maximum range, despite a very similar trend and pattern to supplier 6. Suppliers 9 and 10 have a more cyclical approach as they face orders with higher volumes at different time points and then only receive smaller order volumes from time to time as a buffer against potential customer increases. This allows for a rather more stable order dynamic and pattern, which is not the case for supplier 2, where despite a similar cycle the fill-up orders have a much higher degree of variability, looking for a more troublesome pattern, with more extreme order levels, especially towards the end of the 27 weeks.

Suppliers 7 and 8 follow a mix of cyclical and balanced order patterns and their weekly variations only rarely reach 3-5 times the average level, whereas these peaks then tend to be compensated by slightly lower orders in an overall relatively stable distribution. By far the most stable order patterns are those for suppliers 1, 3, and 4, as the weekly variations compared to the average never go beyond 100% within a demand pattern with the highest level of stability of the entire supplier range.

The average order variation (variation 1) for the 10 suppliers is under 70% (lower than the same indicator for customers), only 2 of the entire range of supplier have averages above 100% in their orders (customers 5 and 6, due to their periodic batch order pattern). On the other hand, suppliers 1 and 3 have order variations below 20%, and supplier 4 has order variations only slightly above 30%, which are very good figures. Other 3 suppliers (7, 8, and 9) have variations of around 50%, also lower than the supplier range average due to their more common cyclical order pattern. The remaining 2 suppliers have a higher range (variation 2), mainly due to the increased variability and higher fluctuation toward the end of the 27 weeks. All in all, except for the higher variability of suppliers 5 and 6, a more stable and balanced order pattern is noticeable. There are differences which can vary from 2 to 5 times depending on the chosen supplier, but the total orders of supplier groups follow a more balanced pattern.

This is also confirmed by the average range in variation between the same data sets for the 10 suppliers. Variation 2 (see Table 4) is less than 220% and 3 times greater than their combined actual average, and supplier 3 had the most balanced difference between these parameters (a 15.18% variation in average orders compared to a 69% maximum variation range), only slightly better than supplier 1 (16.67% for variation 1 and 80% for variation 2). Suppliers with lower average order variations also share lower maximum ranges (in most cases, 3-5 times) as a result of more predictable order patterns with less pronounced fluctuations. It also allows the automotive industry company to have a more reliable supplier base, enabling a better JIT system integration. This is especially important because the company maximizes its production space and warehouse utilization KPIs, therefore reliable suppliers and their deliveries are essential to production planning and order sequencing capabilities in a manufacturing facility that operates at full tilt.

Table 4 presents order variations of the 10 corresponding suppliers and customers within the short loop supply chain of the manufacturing company. The highlighted indicators include the average order level (in units), average order variation (variation 1, in %) and the maximum range (variation 2, in %).

	Average order level [units]	Variation 1 (average) [%]	Variation 2 (max-min) [%]		Average order level [units]	Variation 1 (average) [%]	Variation 2 (max-min) [%]
S1	159	16.67	80	C1	1,425	89.22	296
S2	1,134	58.44	431	C2	204	89.85	567
S3	4,594	15.18	69	C3	67	97.51	249
S4	53,904	30.41	90	C4	2,298	114.18	623
S5	2,222	155.55	250	C5	1,902	36.00	101
S6	624	177.77	700	C6	506	44.44	110
S7	2,297	45.18	105	C7	1,584	52.88	132
S8	13,000	55.18	77	C8	970	176.37	1638
S9	7,823	50.18	154	C9	536	49.44	138
S10	8,208	84.55	220	C10	1,542	41.00	109
Overall average	9,396.5	68.91	217.6	Overall average	1,103.4	79.1	396.3

Table 4 Supplier-customer order variation overview and comparison, by semester

Source: Author

The overall average variation (variation 1) of customer orders (79.1%) was almost 15% greater than the overall average variation of supplier orders (68.9%). Some of the customers had variations up to 6 times greater than their corresponding suppliers (customer 3 and customer 1 had 6.42 and 5.35 times greater variation, respectively), whereas others had around half of that proportion (customer 4 and customer 8 had 3.75 and 3.19 times greater variation, respectively). Customers 2 (53%) and customer 7 (17%) had a smaller ratio of greater variation compared to suppliers 2 and 7. On the other hand, supplier 5 (4.32) and supplier 6 (4.00) had 4 times greater variations than their corresponding customers, and supplier 10 had slightly more than twice (2.06) the variation of customer 10. Supplier 9 and customer 9 had almost a perfect matching variation (50.18% and 49.44%, respectively), while the supplier had a negligible 1.5% greater variation.

The overall average range variation (variation 2) of customer orders (396.3%) was 82% greater than the overall average range variation of supplier orders (217.6%). Some of the customers had variations almost 4 times greater than their corresponding suppliers (customer 3 and customer 1 had 3.6 and 3.7 times greater range variation, respectively), whereas others had an even higher proportion (customer 4 and customer 8 had 6.92 and 21.27 times greater range variation). Customer 2 (31%) and customer 7 (25%) had a smaller ratio of greater range variation compared to suppliers 2 and 7. On the other hand, supplier 5 (2.47) and supplier 10 (2.01) had variations twice as high as their corresponding customers, and supplier 6 had an even greater range variation (6.36) compared to its corresponding customer. Supplier 9 had 11% greater range variation compared to customer 9.

The main parameter used to compare the variations between the supplier and customer data sets is the overall average variation (variation 1 in tables 2 and 3). The value (44.86%) for the entire range of analyzed suppliers (50) was lower than that of the entire range (50) of analyzed customers (58.80%), showing a 31% greater variation in customer order volumes present in this short loop supply chain. When comparing the variations of the supplier-customer corresponding component-part pairs a difference up to 15% in variation was considered stable. A difference in variation above 15% would be considered a BE if variation was greater at the supplier end or an RBE if variation was greater at the customer end. A number of 6 supplier-customer pairs sourced a BE (12%), one pairing with only a 17% difference in variation (marked as a stable BE). Furthermore, 17 supplier-customer pairs (34%) were considered to have a stable relationship as variation between these suppliers and customers was below the set mark of 15%. Other supplier-customer pairs (i.e., 27) sourced an RBE (54%), of which one pair only had a 17% difference in variation and was marked as a stable RBE. Thus for the whole range of 50 suppliercustomer pairings 52% instances were visible RBE situations, 34% were stable and only 10% generated a visible BE. The remaining 4% were marked as stable BE/RBE, as previously shown. These results are in line with current shifts in the automotive industry where carmakers have more and more common suppliers and these tend to become more and more strategically important within the global supply chain and can thus leverage greater negotiating power. As a side note, if the 17 stable instances were also marked as either BE or RBE, 12 of these situations would have a greater customer order variation and hence would have theoretically generated an RBE. In this sense, 39 of the 50 supplier-customer pairings (78%) had greater customer variations than the variations generated within their corresponding suppliers, thus not necessarily supporting typical BE theory and giving way to a new shift of leverage in the automotive industry supply chains.

4. Conclusion

The overall results confirm the existence of both the bullwhip effect (BE) and the reverse bullwhip effect (RBE) in the short loop supply chain of the manufacturing company. A degree of demand variability was 12.64% higher for the 10 analyzed customers (32.74%) than for the corresponding group of suppliers (28.73%), but overall, it was above 30% for all customer-supplier pairings (50). This result confirms the prevalence of the RBE to a greater degree in the analyzed data since 54% of suppliercustomer pairings confirmed clear RBE features in contrast to 12% with signs of the standard BE and a further 34% sourcing for a more stable correlation. The complete range of results showed that 39 out of 50 supplier-customer pairings (78%) had greater variations at the customer end rather than upstream, mostly due to the growing importance, leverage and negotiating power of leading suppliers in the automotive industry. This is also linked with the chip shortage and supply chains still recovering from major fluctuations and uncertainty caused by the pandemic, along with a range of global supply and demand mismatches.

Both the BE and the RBE are detrimental to a company's operational performance and over-

all efficiency, as issues of backlog and/or shortage and excess inventory and/or lack of warehousing space will take up working time and reduce the ability to run the overall logistics operations more smoothly in the already extremely competitive automotive industry. Using a modern EDI system is not enough to ensure reliable data sets, because in addition to real-time and quick information exchange, a real measure of communication is needed to understand the causes of variability. This piece of information would serve as an important input in forecasting demand and help reduce imbalances in the supply chain, reducing also the possibility of late deliveries and the use of more expensive special transport. Besides coordination, internal KPIs must be adequate, reliable and relevant on a larger scale and try to be integrated in more than one workstation or department in order to produce a multiplying effect and achieve a more global optimization, rather than local and/or isolated workstations of high performance. Very good performance levels can also be obtained by considering the needs and challenges of other department teams, and as results are interlinked, this more team-oriented view would also enable a more productive work environment and increase work efficiency in the entire logistics department.

The resulting variations can be further mitigated, especially in this type of short loop supply chain, by an enhanced level of data integration of both downstream and upstream links, making the chain stronger, more agile and resilient. Sharing reliable and relevant coordination data (real-time long-term forecasts, updated planning schedules and frozen periods), as well as qualitative data not visible to a supply chain partner, would help to better adjust internal production parameters (supplier - manufacturer - customer) and reduce both extreme fluctuation peaks and variation intensity during regular production schedules and operations. Within the full report provided to the company, a reduction in variation (of almost 50% over the next 9-18 months) below the 35% margin for its range of suppliers (from a current overall variation of 68%) was quantified, subject to certain adjustments, showing that improvements are possible if an active effort is involved to better synchronize demand and capacity in the short loop supply chain presented.

References

- Boada-Collado, P., Chopra, S. & Smilowitz, K. (2022). The value of information and flexibility with temporal commitments. *Manufacturing & Service Operations Management*, 24(4), 2098-2115. https://doi.org/10.1287/msom.2022.1090
- Brito, G. D., Pinto, P. D. & de Barros, A. D. M. (2020). Reverse bullwhip effect: duality of a dynamic model of Supply Chain. *Independent Journal of Management & Production*, 11(6), 2032-2052. https://doi.org/10.14807/ijmp.v11i6.1043
- Gruchmann, T. & Neukirchen, T. (2019). Horizontal Bullwhip Effect Empirical Insights into the System Dynamics of Automotive Supply Networks. *IFAC PapersOnline*, 52(13), 1266-1271. https://doi.org/10.1016/j.ifacol.2019.11.372
- 4. Krstić, M., Tadić, S. & Zečević, S. (2021). Technological solutions in Logistics 4.0. *Ekonomika* preduzeća, 69(6-7), 385-401. https://doi.org/10.5937/EKOPRE2106385K
- Lücker, F., Chopra, S. & Seifert, R. V. (2021). Mitigating product shortage due to disruptions in multistage supply chains. *Production and Operations Management*, 30(4), 941-964. https://doi.org/10.1111/poms.13286
- Mircetic, D., Rostami-Tabar, B., Nikolicic, S. & Maslaric, M. (2022). Forecasting hierarchical time series in supply chains: an empirical investigation. *International Journal of Production Research*, 60(8), 2514-2533. https://doi.org/10.1080/00207543.2021.1896817
- Nikolicic, S., Maslaric, M., Mircetic, D. & Artene, A. E. (2019). Towards More Efficient Logistic Solutions: Supply Chain Analytics. In *Proceedings of the 4th Logistics International Conference (LOGIC)* (pp. 225-233). Belgrade: University of Belgrade.
- Papanagnou, C. I. (2022). Measuring and eliminating the bullwhip in closed loop supply chains using control theory and Internet of Things. *Annals of Operations Research*, *310*, 153-170. https://doi.org/10.1007/s10479-021-04136-7
- 9. Pastore, E., Alfieri, A. & Zotteri, G. (2019). An empirical investigation on the antecedents of the bullwhip effect: Evidence from the spare parts industry. *International Journal of Production Economics*, 209, 121-133. https://doi.org/10.1016/j.ijpe.2017.08.029
- Ponte, B., Framinan, J. M., Cannella, S. & Dominguez, R. (2020). Quantifying the Bullwhip Effect in closed-loop supply chains: The interplay of information transparencies, return rates, and lead times. *International Journal of Production Economics*, 230, 107798. https://doi.org/10.1016/j.ijpe.2020.107798
- 11. Prajogo, D. & Olhager, J. (2012). Supply chain integration and performance: The effects of long-term relationships, information technology and sharing, and logistics integration. *International Journal of Production Economics*, *135*(1), 514-522. https://doi.org/10.1016/j.ijpe.2011.09.001
- Simchi-Levi, D., Wang, H. & Wei, Y. (2018). Increasing supply chain robustness through process flexibility and inventory. *Production and Operations Management*, 27(8), 1476-1491. https://doi.org/10.1111/poms.12887
- Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P. Y., Combs, K., Ge, Y., Gusikhin, O., Sanders, M. & Zhang, D. (2015). Identifying risks and mitigating disruptions in the automotive supply chain. *Interfaces*, 45(5), 375-390. https://doi.org/10.1287/inte.2015.0804
- 14. Thun, J. H. & Hoenig, D. (2011). An empirical analysis of supply chain risk management in the German automotive industry. *International Journal of Production Economics*, *131*(1), 242-249. https://doi.org/10.1016/j.ijpe.2009.10.010
- 15. Wang, X. & Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. *European Journal of Operational Research*, 250(3), 691-701. https://doi.org/10.1016/j.ejor.2015.07.022