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# ON THE IMPACT OF ORDER VOLATILITY IN THE EUROPEAN AUTOMOTIVE SECTOR

*Childerhouse, P.,* [1*] *Disney, S.M.,*[2] *and Towill, D.R.* [2]

[1*] Department of Management Systems, Waikato Management School, The University of Waikato, Private Bag 3105, Hamilton, New Zealand.
e-mail: pchilder@mngt.waikato.ac.nz (*Corresponding Author)

[2] Logistics Systems Dynamics Group, Cardiff University, Cardiff Business School, Aberconway Building, Colum Drive, Cardiff, CF10 3EU
e-mail: DisneySM@Cardiff.ac.uk

**Abstract**

Order volatility is an unfortunate fact of life facing most suppliers of both products and services. In this paper we are concerned with establishing the magnitude of the problem faced by the European automotive sector. The evidence has been acquired via the site based Quick Scan Audit Methodology (QSAM). Production scheduler strategy is thereby classified according to a new five set schema as observed via individual value stream volatilities. System variables have then been codified and correlated with customer order volatility. Powerful statistically significant relationships emerge from this evidence. This generally (but not wholly) supports intrinsic views on what constitutes good practice. A specific interface between supplier and OEM shows the existence of a positive loop which acts as a vicious circle to create unnecessary volatility in material flow.

**Key words:-** Supply Chain Audit; Vicious Circles; Scheduler Strategies; Bullwhip.

## 1. Introduction

Order volatility may induce bullwhip in which production orders are subject to more lively behaviour than the incoming customer demand. However, although demand amplification has been studied via simulation (Forrester, 1958), using OR type analysis (Lee et al., 1997, who in passing coined the "bullwhip" phrase), and utilising transfer function modelling (Dejonckheere et al., 2002), there have been relatively few industrial research studies to promulgate and exploit this knowledge. Notable exceptions are in the in-depth case studies described by Harrison (1996) and McCullen and Towill (2002). Unusually, the latter paper also evaluated the beneficial impact of system design changes on bullwhip and inventory variances as recorded consequent to the execution of an effective BPR programme. As Metters (1997) has shown, the cost of bullwhip can be extremely high. Nor are higher inventories necessarily part of the answer, since it may well be that the wrong parts are in stock. Hence the well known counterintuitive result that customer service goes down as holding costs increase.

The earlier work by Harrison (1996), clearly illuminated the magnitude of the problems caused by schedule volatility. A very relevant horizontal survey was later conducted by Liker and Wu (2000), comparing US and Japanese automotive OEMs, the data of particular interest to our research being portrayed in Figure 1. Clearly, the streamline flow principles customarily followed by the three Japanese automakers has resulted in far less schedule volatility for their suppliers, especially in the short term. At that time there appeared to be an order of magnitude to be overcome before the US auto suppliers achieved parity. Since the same marketplace is targeted by both groups of OEM, it is obvious that the material pipelines must generate this schedule volatility internally. More recently, Schonberger (2007) has argued that in aiming to counter this situation, some American companies may actually have the advantage. An example he quotes is the opportunity to exploit their apparent skill advantage of re-structuring ready to meet the next generation of marketplace challenges.

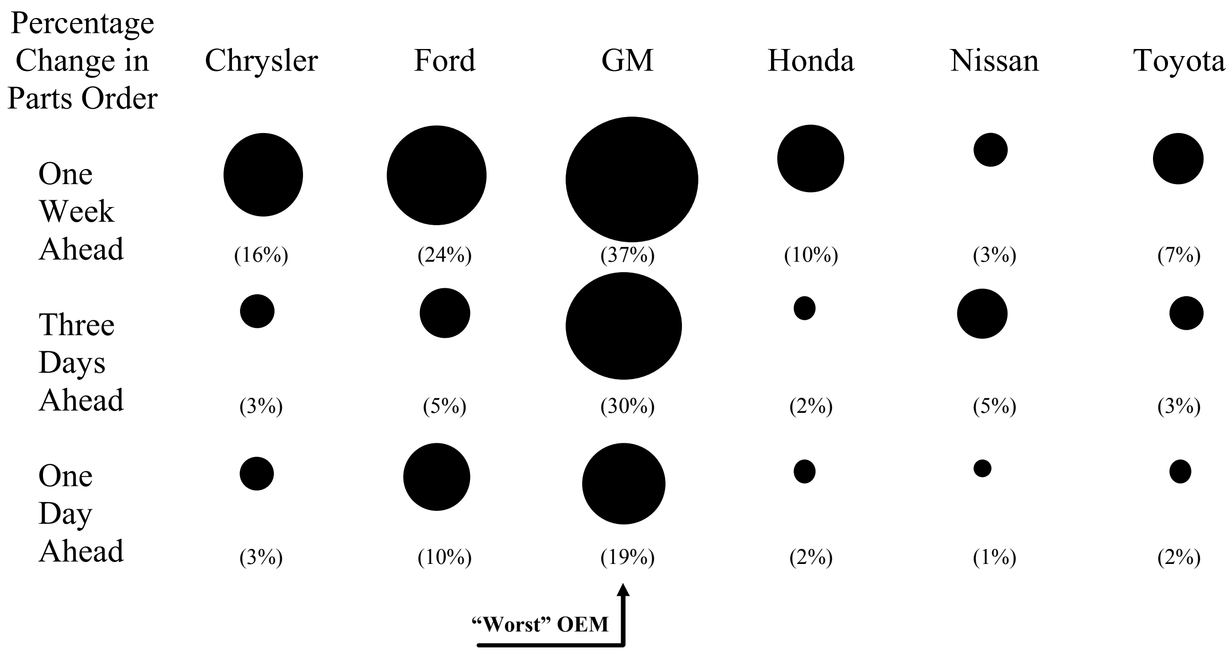


**Figure 1. Summary of Order Volatility Induced by US and Japanese Implant Automakers via Late Changes**
(Source: Authors, based on data by Liker and Wu, 2000)

## 2. Automotive Sector Supply Chain

In this paper we focus on the European Automotive Sector, and influences on its order volatility scenarios. A recent statistical analysis of the Japanese vehicle industry has shown that in the vast majority of products studied, significant production smoothing is highly evident (Mollick, 2004). Of particular interest is the fact his seminal research indicates that two-thirds of the individual vehicle sectors demonstrate significant on-costs. These result from production deviations necessitating ramp-up/ramp-down behaviour to meet volatile schedules. Hence appropriate production scheduling is seen as a key factor in vehicle manufacture business strategy.

Of course, the real-world range of possible resultant schedule dynamics is very wide. At one end of the spectrum the aim is to level schedule, which in effect is making to inventory even if the target is *relatively* stockless and is adjusted periodically in the light of sales trends. This approach is heavily dependent on customer collaboration if the delivery process is to be sufficiently smooth (Suzaki, 1987). At the other extreme the response appears chaotic, at least to the casual observer. We shall meet both in our sample, and a number of variants in between.

## 3. Production Scheduler Influences

The various influences on a production scheduler as observed engaged in the real-world automotive industry may be modelled as a input-output diagram as shown in Figure 2 (Olsmats et al., 1988). It is a careful and stressful balancing task even when strongly supported via appropriate Decision Support Systems (DSS). As input, there are actual orders from a range of customers. Some will have provided reasonably accurate and stable forecasts. Others will offer only poor initial forecasts and volatile late changes, as we have already seen from the US survey by Liker and Wu, (2000). But there are many other influences on the scheduler such as market intelligence, customer service policies, contingencies and trend detection. An especially important problem is that the delivery process (whether internal or external) is itself excessively variable. This feedback will also affect decision-making to decide what orders are placed by the scheduler on "his" shop floor.

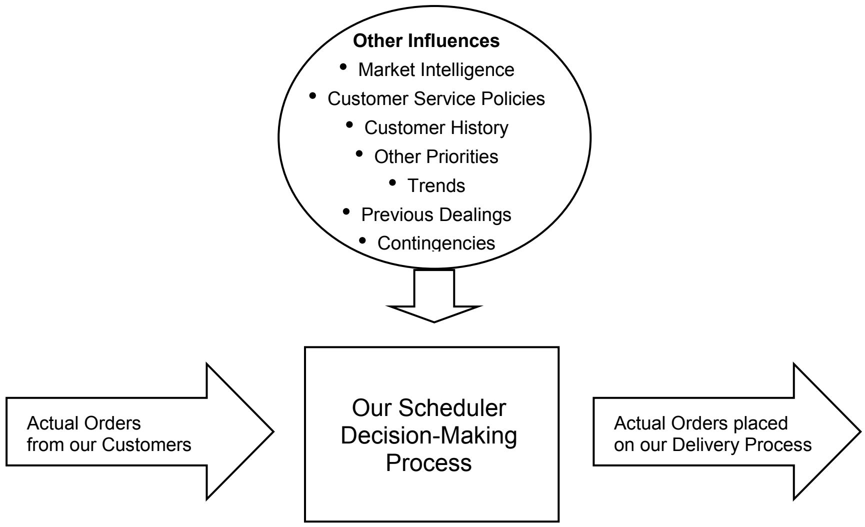


**Figure 2. Input-Output Model of the Production Scheduler Decision-Making Process**
(Source: Authors, based on Olsmats et al., 1988)

Internal activities may themselves result in "vicious circles" which the production scheduler must be aware of. For example, Figure 3 shows a posited industrial situation with two self-enhancing feedback loops which can considerably affect delivery performance (Hoover et al., 1996). As we have shown elsewhere, there is a well trodden process re-engineering path to be followed in resolving this situation (Towill and Childerhouse, 2006). It is essential to first bring one's "own activities" under defect free control so that what the scheduler actually orders is delivered right and on time. Hence the planning/inventory and quality loops in Figure 3 must be determinedly blitzed if this uncertainty pathway is to be removed.

Note that the range of problems arising in the multi-product scenario can be somewhat different from the aggregate statistics shown in Dejonckheere et al. (2003) and, require considerable care in any subsequent analysis (Fransoo and Wouters, 2000). Certainly there is some industrial evidence to support the view that schedulers may reasonably balance such conflicting demands even if, as a consequence, individual value-stream volatility may be somewhat increased. Furthermore, in complex supply chain scenarios, the scheduler may be reasonably but informally aware of what is actually happening at the marketplace despite demand amplification

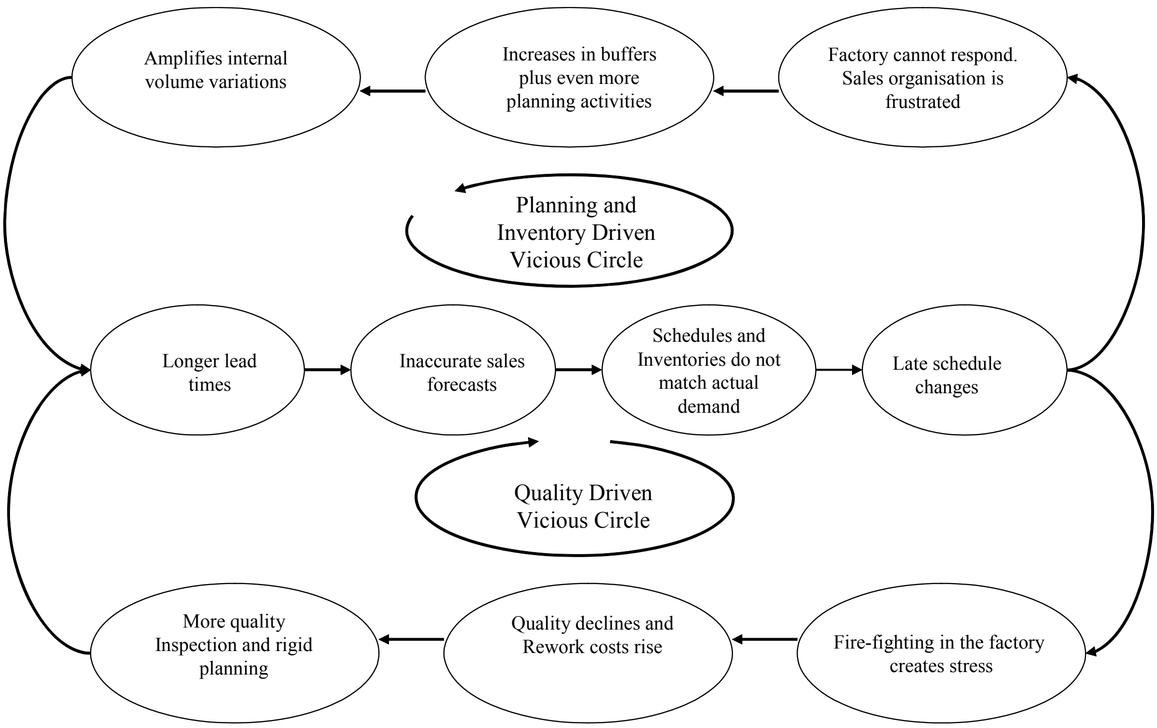


**Figure 3. Chaotic Behaviour Caused by Self-Enhancing Feedback Loops**
(Source: Authors, based on Hoover et al., 1996)

in orders being induced by downstream "players". For example, Holmström, (1997) highlights some dynamic behaviour observed in a multi-production European confectionary chain which is almost certainly due to such an overview. In this particular case, the scheduler acts to smooth production for high selling items. However, as a consequence, he is prepared to induce volatility in the pattern of manufacture for the lower selling products.

## 4. Contribution of This Paper

This paper aims to increase the knowledge base on order volatility as observed in real-world value streams. The novel contribution herein is the study across a sample of enterprises so that the phenomenon can be evaluated on a comparative basis. Twenty two European automotive value streams are assessed to investigate the volatility effects. This is enabled via the development of a five level classification schema by which the production scheduler strategy may be categorised. The results confirm that previously identified best practice companies (Towill and Childerhouse 2006) minimise schedule volatility in order to avoid costly ramifications. Attention has been concentrated at the impact of customer order volatility on the subsequent actions by the production scheduler. This model is based on knowledge obtained from an earlier in-depth case study in the UK automotive industry (Olsmats et al. 1988). That paper included simulation modelling to predict behaviour in response to typical demands, such a procedure exploited herein to explore the range of experienced scheduler responses.

Many sources have influenced this investigation. They include vertical Case Studies (Harrison, 1996, and Thaler, 2001), horizontal surveys (Liker and Wu, 2000), and site-based Quick Scan Audit Methodology (QSAM) (Naim et al., 2002). The last named approach combines some important elements of case study outputs but carried out on a sample large enough to undertake statistical analysis. Available records and observations acquired during QSAM are used to assess volatility on both sides of the production scheduler decision-making process. This provides the necessary information to estimate the value stream position in the scheduler strategy classification matrix.

By multi-sourcing in this way, it is expected that the research conclusions reported herein will satisfy the many conflicting criteria and viewpoints previously expressed in the literature by Eisenhardt (1989), Dyer and Wilkins (1991), Bergtsson et al. (1997), and Ottosson and Borg (2004). An in-depth description of QSAM and how it is applied on a typical industrial site is described in depth by Naim et al. (2002), and will not be repeated here. In this paper, the goal is to use QSAM to generate the necessary data to test for significant system variables affecting schedule volatility. It is further used to provide the evidence that a "vicious circle" operates across a particular supplier-OEM interface.

## 5. Proposed Classification Scheme

Five possible rational groupings of value stream operations emerge based on the scheduler strategy. These policies are posited as chaotic; demand amplification; pass orders along; demand smoothing; and level scheduling. We argue that such a diversion may be broadly related to the actual industrial practices observed by Buxey (2001), and previously delineated by Dejonckheere et al. (2003). It may also be supported via exploiting well established simulation models under very specific operating conditions. Figure 4 shows these five categories superimposed on a customer order volatility versus production planning volatility matrix.

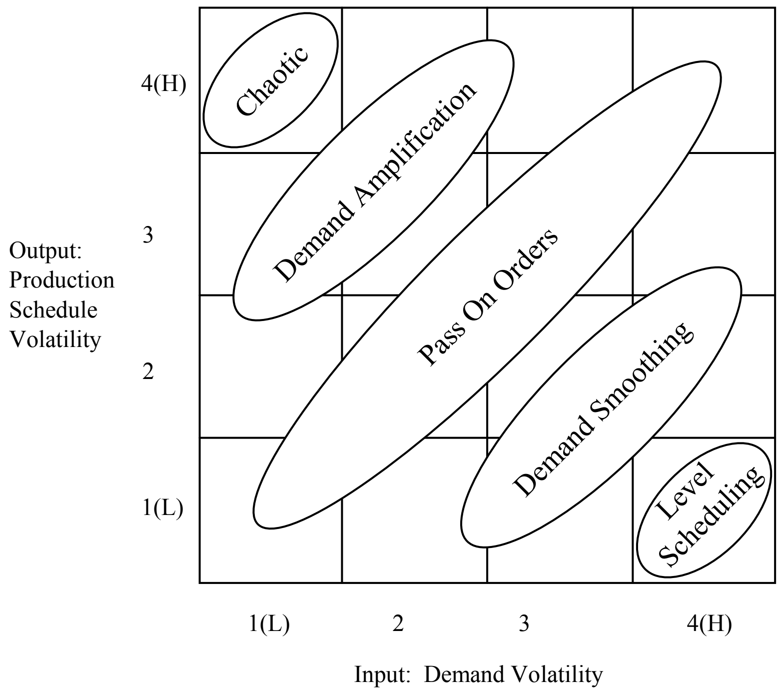


**Figure 4. Categorization of Posited Production Scheduler Strategies**
(Source: Authors)

In our classification scheme for the production scheduler strategy, we have included an extreme pattern of behaviour. This we have termed "chaotic", but in the particular sense defined by Burger and Starbird (2005). In other words, there is an apparent state of utter confusion or disorder. It is *possible* that the latter behaviour may also be chaotic in the mathematical sense. The latter is a process which exhibits chaos, but is highly dependent on the initial starting point. Furthermore, slight differences in the initial conditions can lead to vastly different responses and often extremely confusing responses.

Note also that Pass Orders Along (POA) is of particular interest herein, since it is a benchmark originally developed by Sterman (1989). He found that 75% of a large sample of Beer Game "players" performed worse than PAO as judged against his selected trade-off criterion. So, whilst it is not necessarily a good tactic to adopt in any particular situation, there are arguably much worse actions which might be taken. We shall now see that even with relatively simple system models we can readily generate a powerful set of responses offering considerable insight into dynamic behaviour.

The major alternatives for schedule behaviour are illustrated in Figure 5. Plot (a)-(e) shows simulated responses based on Forrester effects generated within the system (Disney and Towill, 2003). Graph (a) is an unstable response that represents an extreme case of chaotic behaviour. Graph (b) shows a serious bullwhip effect, where the variance of the replenishment orders is significantly larger than the variance of demand. Graph (c) highlights a system which very nearly simply passes on the customer orders. Graph (d) shows a case where the variance of the replenishment orders is significantly less than the variance of demand. Graph (e) demonstrates a level scheduling approach based on aggregate long term demand. In comparison, plot (f) shows the real-world sales data and actual orders placed within the UK grocery industry (Hines and Rich, 1997). We should, therefore, not be surprised at the comparable range of scheduler outputs emanating from site-based QSAM studies.

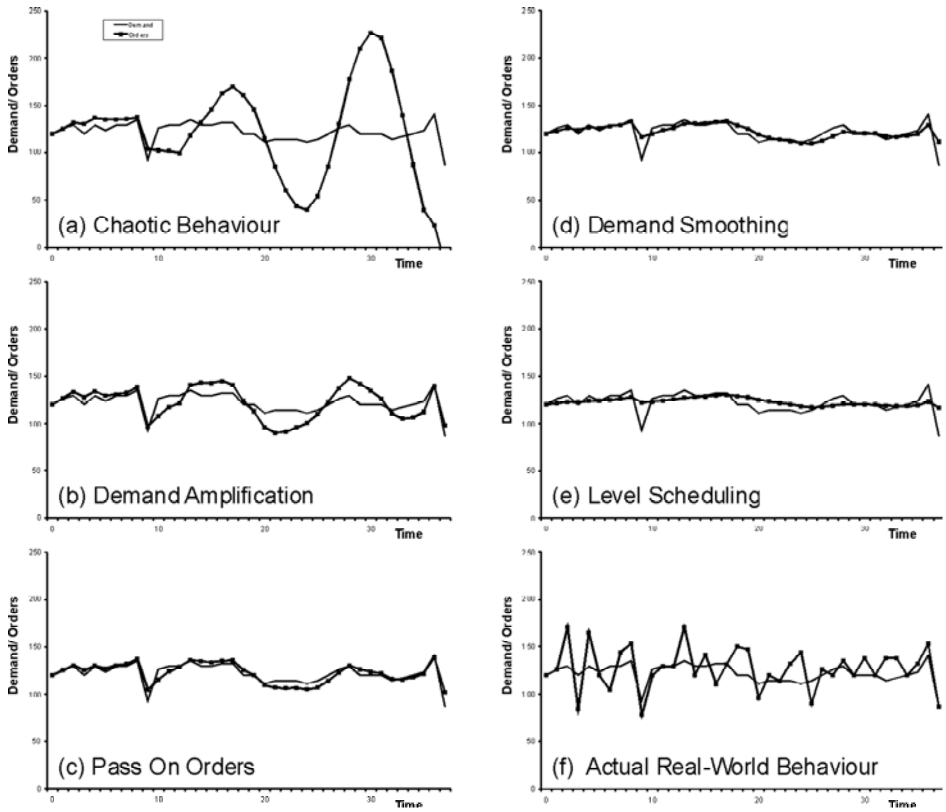


**Figure 5. Simulated Responses showing how Various Replenishment Algorithms respond to Schedule Volatility**
(Source: Authors)

## 6. Industrial Investigations

The majority of European automotive value streams included in our particular sample are located at the first tier suppliers to OEM level. In other words, those supply chains are directly comparable with those surveyed by Liker and Wu (2000). However, in some cases it was also possible to audit second tier suppliers. Customer Order Volatility for the European automotive value stream sample is plotted in Figure 6 and is based on the accuracy of one month ahead forecasts when compared to actual call-offs on the delivery day. In the automotive sector, the one month ahead forecast is typically provided by the customer (OEM) and can be considered a rough estimate of scheduled demand. Our average volatilities are calculated from twenty-six sequential weekly data points consisting of daily sales and forecast demand one month ahead for each nominated product. The process of calculating the order inaccuracy is simple. Once the two columns of data (forecast and actual) have been inputted into a spreadsheet, the forecasts are aligned to the resultant actual for each corresponding day and average differences between the two thereby calculated.

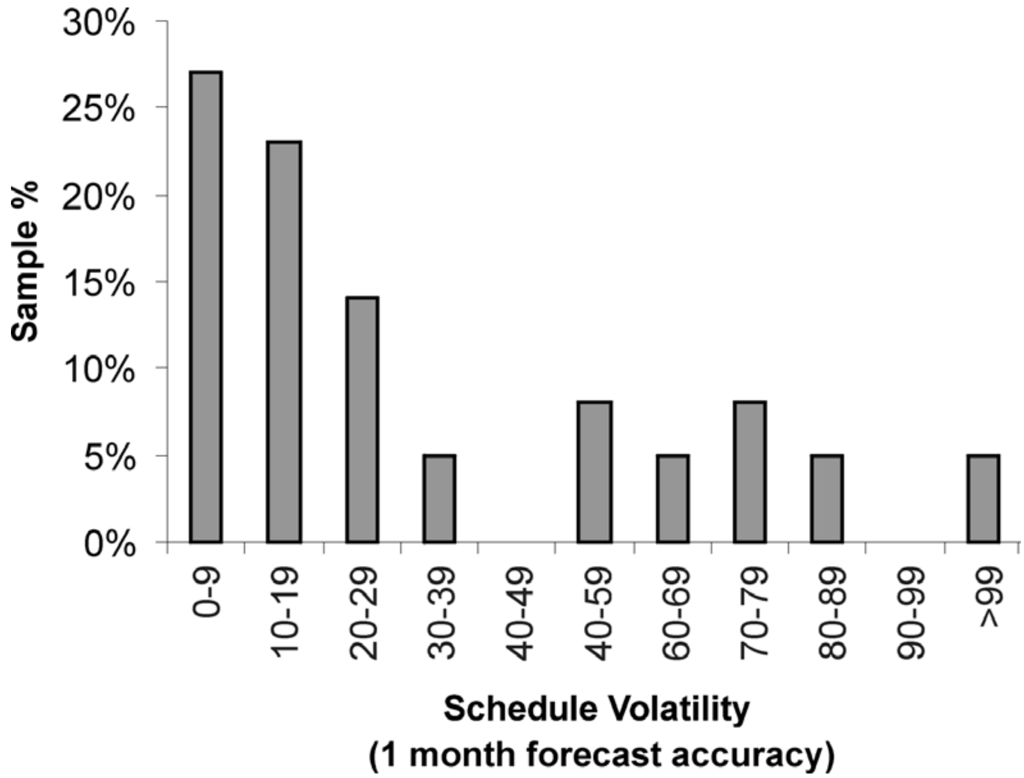


**Figure 6. Customer Order Volatility Histogram for European Automotive Sector Value Stream Sample**
(Source: Authors)

Note that there is a very large spread of results for the customer order volatility as estimated via this process. However, 50% of our sample lie within the 20% range. Importantly both Japanese implants studied are within a few percentage points of the origin. This is to be expected as it agrees well with previous conclusions reached by Harrison (1996) and Liker and Wu (2000). Hence from this particular view point the schedulers' task in dealing with an individual customer is greatly simplified.

In order to populate our volatility matrix previously illustrated in Figure 4, the production planning volatility was also assessed for the twenty-two value streams. It is not possible to use a quantitative measure for this variable due to the vast differences in production facilities, product ranges, capacity limits and lead time constraints of real world supply chains. Rather, an overall comparable measure has been developed based around the assessment of control uncertainty caused by the planning and scheduling process. The level of production planning volatility was codified from a wide range of data collected during each of the supply chain audits, including, but not limited to, levels in the BOM, daily call-offs, supplier orders and delivery performance, process lead times, kanban logic, batching rules, MRP logic, product variants, delivery frequency, complexity of material flow, levels of waste and number of competing value streams. The resultant categorisation of the automotive sample is illustrated in Table 1.

**Table 1. Five Category Classification of Automotive Sector Production Scheduler Strategies**

| Scheduler Classification Strategy | Value Stream Code No. | Comments On Particular European Automotive Sector Examples |
|---|---|---|
| • Chaotic | (13), (16), (17) | • Value stream 17 has both internal and external customers, the process has variable yield rates and expediting product is commonplace. |
| • Demand Amplifications | (22), (1), (8) | • Value stream 1 has relatively stable OEM customer demand but places highly variable demand on most of its suppliers. |
| • Pass Orders Along | (9), (12), (6), (5), (20), (21), (4), (11), (10), (8) | • Value streams 4 and 5 serve Japanese implants: the demand is predictable and the supply is co-ordinated by the customers. |
| • Demand Smoothing | (3), (2), (14), (15), (17) | • Value streams 14 and 15 are forging processes with the raw material common for many products, hence polling has allowed some smoothing of the dynamics. |
| • Level Scheduling | (19) | • Value stream 19 is a third party logistics provider and levels its automotive customer's demands before placing them on the automotive parts supplier. |

Somewhat unsurprisingly nearly half of the sample is positioned in the pass orders along category in Table 1. More worryingly are the six cases of increased volatility, i.e. those in the chaotic and demand amplification categories. The production planners in these cases are increasing the volatility to the detriment of internal and upstream supply chain members. Thankfully, there are also six good cases in our sample that are dampening the input volatility. Further insight from one or two cases in each of the strategy types that verifies the analytical categorization is provided in Table 1.

## 7. Automotive Sector Statistical Analysis

Table 2 clearly highlights the many plausible effects of schedule volatility on the performance of a supply chain and possible causes of the schedule volatility itself. Also added are comments generally found relevant to improving value stream performance. Three of the variables correlate at the very highly significant level of 99%, two of which, system induced behaviour and demand amplification, highlight possible causes of any schedule volatility. The former is displayed as a boxplot in

Figure 7 and clearly shows those that suffer from demand amplification (represented by the number 1 in Figure 7) have, on average, over five times the level of schedule volatility. Figure 7 also contains a boxplot of another 99% correlated variable, duration of product life cycle. In this instance, those products with long life cycles (represented by the number 4 in Figure 7) suffer from significantly less schedule volatility that those with shorter life cycles (represented by the number 1 in Figure 7). This is perhaps due to better market knowledge and more stable, long term market conditions.

**Table 2. Ranking the Statistical Relationships Established Between "Our Customer" Order Volatility and Value Stream Variables**

| Statistical Significance Level | Value Stream Variables | Direction | Comments |
|---|---|---|---|
| 99% | System induced behaviour observed in demand | + (as expected) | • Improve working relationship with all "downstream" players |
| | Excessive demand amplification | + (as expected) | • Improve working relationship with "our" customer |
| | Life cycle duration | - (as expected) | • Possible penalty induced by "demanding" marketplace |
| 95% | Supplier relationship | - (as expected) | • Unnecessary problem eradicated by better liaison |
| | Supplier delivery frequency | + (as expected) | • Possible penalty to be paid for JIT |
| | Demand uncertainty | + (as expected) | • Can be reduced by better sharing of marketing information |
| | Causal relationships often well separated in time | - (counter intuitive) | • Reduce via TCTC and EDI practices |
| | Variable performance in response to similar orders | + (as expected) | • Self-learning software may help |
| 90% | Poor and variable customer service levels | + (as expected) | • Check that "lean production" actually happens |
| | Product variety | + (as expected) | • Possible penalty induced by "demanding" marketplace |
| | Stage of life cycle | - (as expected) | • Life cycle dynamics becomes part of DSS |
| | Complicated material flow patterns | - (as expected) | • Use GT to streamline product flows |
| | Poor stores control | + (as expected) | • Better stock control and systems discipline |

Five variables correlate at the 95% or greater statistically significant level in Table 2. Supplier relationships are negatively correlated with schedule volatility in this instance at the 97% significance level, with those value streams with arm's length relationships often having to deal with unstable demand schedules. This inter-relationship is displayed in boxplot form in Figure 7 and clearly shows the stepwise decrease of schedule volatility with increased supplier relationship proximity (1 in the diagram represents an arm's-length relationship whilst 4 denotes a partnership). The number of deliveries per month correlates positively with schedule volatility, this may be a mechanism to cope with the instability. Demand uncertainty is significantly related to the volatility in demand schedules. This correlation is once more displayed as a boxplot in Figure 7 and clearly shows that those with low uncertainty (represented by the number 1 in Figure 7) have very stable schedules and, in contrast, those with high uncertainty (represented by the number 4 in Figure 7) have variable levels of schedule volatility. Intriguingly, the delay between cause and effect is less in circumstances of high schedule volatility, why this is the case requires further investigation. The fifth variable that correlates at the 95% level is the positive relationship between the inconstancy of performance and high schedule volatility.

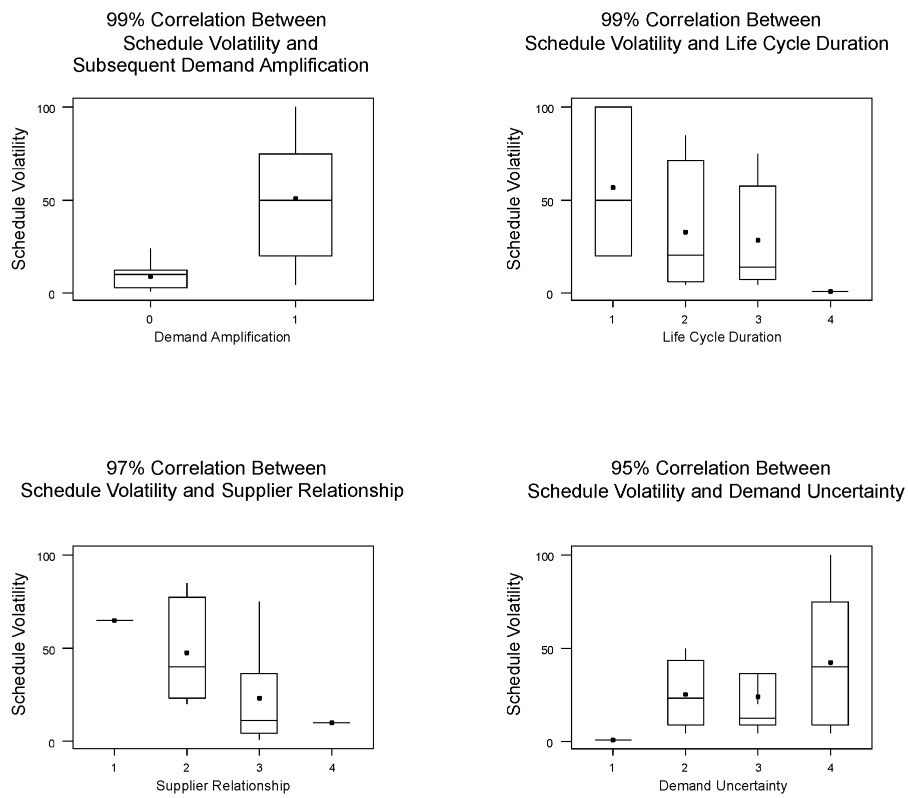


**Figure 7. Boxplot Displays of Four Automotive Value Stream Factors which are Highly Correlated with Schedule Volatility**
(Source: Authors)

## 8. Further On-Site Observed Interactions

The opportunity arose to conduct two (material flow sequential) Quick Scans on a OEM plus one of their associated component suppliers. The specific aim was then to investigate how demand amplification was affecting the supply chain and the causes of apparently poor schedule adherence on the part of the component supplier. Four researchers and associated company staff conducted the audit, following an intensive two days on-site data collection at each plant. Effort was then focused on identifying the root causes of the observed excessive volatility. As part of the modelling phase this led to the development of the cause-and-effect diagram, shown here as Figure 8. This clearly illustrates that the poor schedule adherence was not only due to the supplier performance, but was also partially caused by the customer altering the schedule. As a side-benefit to the company, the Quick Scan team was able to act as a facilitator in rectifying the problem. This is in contrast to the customary way of promoting a blame culture between customer and supplier.

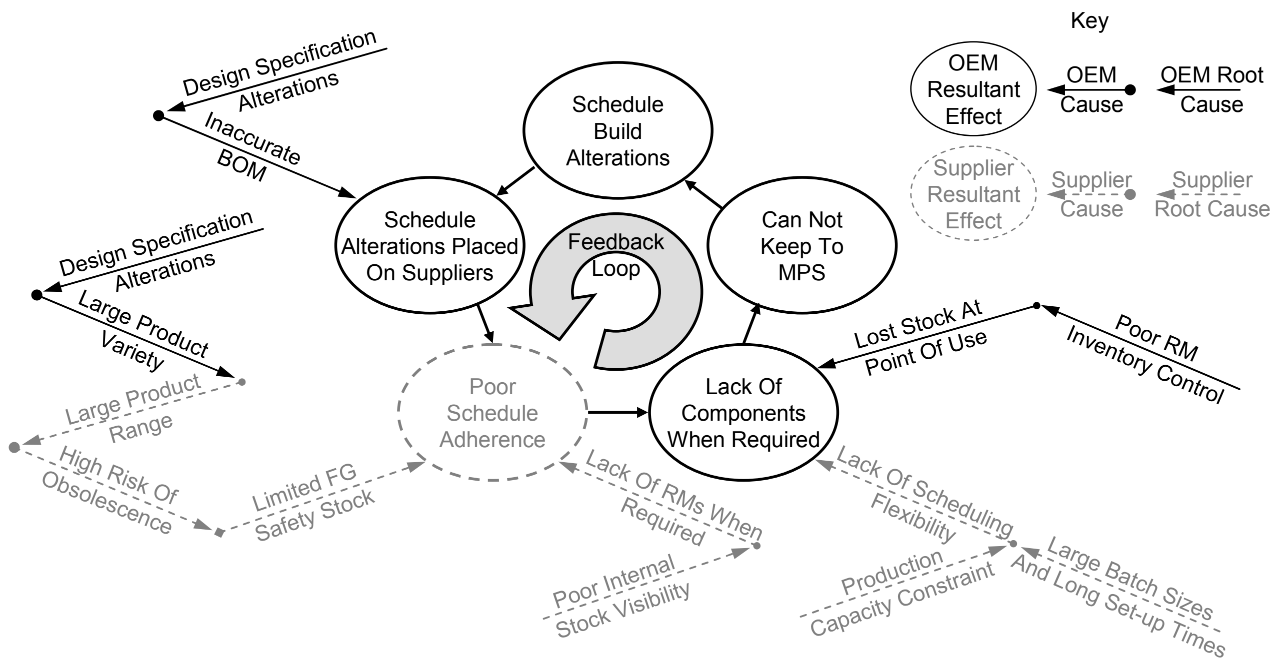


**Figure 8. Cause-and-Effect Diagram demonstrates Self-Enhancing Behaviour identified via QSAM Studies Supplier-OEM Value Streams**
(Source: Authors, based on Childerhouse, 2002)

Significantly, self-enhancing feedback loops areas are apparent in the model structure, as illustrated in Figure 8. These are generally similar in nature to those general descriptors met in Figure 3. However, in this particular supplier-OEM Case, the resulting vicious circle clearly extends over the business interfaces. Manifestly poor schedule adherence on the part of the supplier results in lack of components being available when they are required for assembly by the customer. This in turn results in the engine assembler having to change their build plan because they cannot build the scheduled engines. These changes in the schedule in turn also affect the supplier and hence the positive loop is completed because the supplier finds it difficult to adhere to the constantly changing schedule. Consequently, following this audit the main opportunities for improvement in value stream performance were focused on breaking this positive feedback loop and hence significantly improving the relationship between customer and supplier.

## 9. Discussion on Perceived Scheduler Strategy

Are the results shown in Table 1 completely unexpected, or do they correspond to strategies historically likely to be associated with a traditionally aggressive market sector? After all, each value stream studied was a major source of business to the companies concerned. They certainly did not fit into the category of "top-up" products taken on board to utilise spare capacity. Quite the reverse, since the product families thus evaluated were very much "core business". Interestingly, the production scheduler strategy in nearly 50% of the cases was pass orders along. In other words, the value stream flow was not significantly changed in its nature by the actions of the controller. Hence, if our customer's order pattern was relatively smooth, then the production plans were very similar. Likewise, in some instances where the customer orders were highly volatile, and this in turn was reflected in the production planning activity i.e. passed on with little modification.

Another way of looking at scheduler strategy is simply to take a broad brush approach. This means asking the basic question: Is the production planning volatility greater than; about equal to; or worse than customer order volatility? It is a rather crude classification, but our automotive sample does generate some rather interesting but simple statistics. Almost half of the value streams have volatility observed to be about the same both sides of the scheduler DSS. About one quarter of the sample has at least some degree of demand smoothing with the production plan protected against exterior volatility. The remaining quarter of the production schedulers induced greater volatility on the production plan than would be expected from the pattern of customer orders. In extreme cases, such behaviour could be termed “chaotic”.

Two other pieces of research help considerably in explaining the wide spectrum of results reported herein. Chen et al. (2005) surveyed 7,295 US firms and assessed changes in their inventory levels over the twenty year period 1981 to 2000. Despite extensive “Japanisation” of companies during this period (Schonberger, 2007) and the consequential pressure to reduce waste, in the 61,058 observations of Chen et al. (2005), the estimated reduction in median stock levels were:

- Raw material ~ 35 days → 28 days (down 20%);
- Work in process ~ 22 days → 9 days (down 59%);
- Finished goods ~ 39 days → 31 days (down 6%).

In other words, the total impact of the huge number of business improvement programmes undertaken in industry over twenty years, has been to output a substantial reduction in WIP (“our” process), and a reasonable reduction in raw materials (“supply” side). However, there has been little noticeable change in finished goods stocks (“demand” side). This can be due in part to unpredictable orders from our customer, but exacerbated by the poor level of information exchange between the two parties.

Secondly, our earlier research (Towill and Childerhouse, 2006) has established that there is a well-trodden path to value stream improvement which we believe is cognate with the output of Chen et al. (2005). This evidence suggests that companies make reasonable effort to bring their “own process” under control. This means reducing defect rates, breakdowns, shortages and set-up procedures so that what the production scheduler orders is actually delivered fault-free when required. At this stage, there should be significant reductions in WIP, exactly as recorded by Chen et al. (2005). The host company then has both the knowledge and experience to work with their own suppliers and move towards a more reliable JIT delivery service. Consequently, the raw material stocks are reduced, as Chen et al. (2005) have also shown. Finally, the company can seek to work more closely with its downstream customer. But so far, according to this extensive survey this has had little impact, except in “special” situations. As Suzaki (1987) said, such collaboration downstream has to be worked on in an effective and sustained way. It does not come as a “given”. However, the US Japanese implants in Table 1 (Liker and Wu, 2000) apparently come near to this ideal state.

## 10. Conclusions

Despite much evidence supporting the “smooth is smart” operational objectives, turbulence is still a problem in automotive supply chains. Nevertheless, best practice automotive OEMs do minimise their order volatility. This reduces the significant ramp-up and ramp-down costs for their suppliers and hence benefits the supply chain as a whole. Our study of twenty two European automotive value streams has additionally identified a number of other factors that relate to schedule volatility in addition to the obvious increase in demand uncertainty. Statistically significant correlations have been established between demand amplification, and poor supplier relationships and, amongst other factors, low and indifferent service levels. The resultant ramifications of high customer order volatility were then investigated via a dyadic supply chain relationship case study. A real-world positive feedback loop was identified that highlights the ever increasing problems of customer schedule volatility and poor supplier deliveries performance. This “vicious circle” extended across the customer supplier interface and hence illustrates well the narrative descriptions of this phenomenon which have previously appeared in the literature.

A future research programme is targeted to exploit the methodology developed herein to study order volatility in other market sectors. Preliminary tests suggest that, contrary to some perceived wisdom, this phenomenon is not unique to the automotive industry. What will be particularly interesting will be the subsequent statistical analysis concerning system variables. Only further evidence will confirm if similar causal relationships exist elsewhere. Once this has been established it will be possible to posit further “new management theory” based on order volatility which is likely to pass the transferability test proposed by Micklethwait and Woolridge, (1996). If so, then some of the solutions discussed herein may become similarly universal in applicability.

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