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Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect

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The bullwhip effect is causing inefficiencies in today's supply chains. This study deals with the potential of big data on the improvement of the various supply chain processes. The aim of this paper is to elaborate which characteristic of big data (lever) has the greatest potential to mitigate the bullwhip effect. From previous research, starting points for big data applications are derived. By using an existing system dynamics model, the big data levers 'velocity', 'volume' and 'variety' are transferred into a simulation. Overall, positive impacts of all the big data levers are elaborated. Findings suggest that the data property 'velocity' relatively bears the greatest potential to enhance performance. The results of this research will help in justifying the application of big data in supply chain management. The paper contributes to the literature by operationalising big data in the control engineering analyses.

Keywords: bullwhip effect; simulation; control charts; forecasting; big data levers

1. Introduction

1.1 *Initial situation*

In the field of supply chain management (SCM), companies are still facing the problem of the bullwhip effect, which causes inefficiencies among the various channels (c.f. Lee, Padmanabhan, and Whang 1997a). Previous approaches have already tried to reduce this negative effect by introducing computer systems (c.f. Mason-Jones and Towill 1999) or by implementing different replenishment rules (Dejonckheere et al. 2003). A major cause of the bullwhip effect is the process by which supply chain decisions are made. Such as demand forecasting, supply chain decisions are often carried out under uncertainty (Chen et al. 2000), which means they lack adequate information (e.g. given demand in a period). Due to this reason, a focus was placed on big data. Big data applications can complement decision support systems (DSS), foster complex decision-making and help problem solving in the supply chain (Shim et al. 2002). By mitigating the bullwhip effect, a key role may be seen in information enrichment (Dejonckheere et al. 2004) or information sharing (Yao and Dresner 2008).

Collecting and applying big data supposedly offers potential to improve business processes. For example, Russom (2011) perspicuously noticed that 70% of the questioned business experts think of big data as an opportunity for business advantage (13). While there seems to be huge potential for big data applications[1] in various sectors – from manufacturing to health care in general (Manyika et al. 2011) – it could be particularly interesting to look at a field where not one, but many functions, processes and actions in and across organisations are affected. An area where this is especially true is the field of SCM. Despite Waller and Fawcett's (2013) belief that big data has the power to thoroughly change the rules of decision-making in SCM, little research has been conducted to deepen the understanding of how big data applications may affect the supply chain. Even more, it is unclear which characteristic of big data has the largest impact on SCM.

Closing this research gap, this paper tries to incorporate big data applications in supply chain decisions via an operationalisation in bullwhip simulations. Guiding *research questions* include the following: does big data help to mitigate the bullwhip effect? If so, which of its characteristics (levers) have the greatest potential?

1.2 *Research design*

The aim of this study is to operationalise big data in supply chain decisions in order to mitigate the bullwhip effect. This paper tries to find out which 'starting point' – as areas of improvement – is most promising. Further the paper investigates on which characteristic potential big data applications should be focused on.

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The basis for these starting points is laid by a review of the past and current literature on SCM in the context of the *bullwhip effect,* as well as on the topic of *big data*. Since the evolution and creation of new knowledge is generally generated through the process of accumulation, the review of related literature is an essential basis for any scientific project (Baker 2000, 219). The desired outcomes of this review include (i) relevant big data levers and (ii) the causes and corresponding problems of the bullwhip effect. The analysis of the former mitigation approaches should then bring up (iii) ideas on how different data types (big data levers) can enhance supply chain decisions.

Applying the control theory (Dejonckheere et al. 2003), a simple model with block diagram simulations can be conducted to show the impact of big data levers on the bullwhip effect. The purpose of such analysis is to highlight several potential touch points of big data applications in supply chain decisions. Subsequently, direct effects on the intensity of order distortion as well as indirect effects on net stock levels will be analysed. Single big data levers are operationalised as independent (control) variables influencing the degree of supply chain decisions (outcome expressed by the bullwhip measure). All in all, this paper is based on the assumption that big data can be perfectly dealt with in theory. The only restricting factor is a firm's ability to do so in practice.

The paper is organised as follows: the following section discusses the foundations and terminologies, along with the causes of the bullwhip effect and former mitigation approaches. By synthesising previous research, starting points for big data levers are defined. Then, an existing system dynamics model is introduced and adjusted for the purpose of this research. Additionally, the starting points are transferred into the model and simulations are performed using MATLAB. The last section summarises the findings and presents some final recommendations.

2. Literature review

2.1 *Big data*

A quick, non-representative research on Google Trends for the keywords SCM, cloud computing and big data underlines the topicality of the area of interest. In Figure 1, it can be seen that the already established term SCM shows a relatively stable trend line over the whole period. The other two terms did not exist at the beginning of the analysis. The interest in cloud computing grew abruptly from about 2008 to 2010 compared to the interest in big data. Starting in 2011, however, big data had a significantly higher interest recorded compared to other terms.

In a recent report, Brown et al. (2011) states, 'Big data refers to data sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse' (1). Similarly, Jacobs (2009) explains that big data is about 'data whose size forces us to look beyond the tried-and-true methods that are prevalent at that time' (44). Both definitions include the idea of big data being something that cannot be processed today using conventional equipment or methods. This statement also implies that 'data we consider big today may not be considered big tomorrow due to the advances in processing, storage and other system capabilities' (Zaslavsky, Perera, and Georgakopoulos 2012, 22). Following Cukier and Mayer-Schönberger (2013), big data can also be defined as 'the ability of society to harness information in novel ways to produce useful insights or goods and services of significant value' (2). With regard to businesses, such insights may be an opportunity to take management to the next level. As Brynjolfsson and McAfee (2012) put it, 'Data-driven decisions are better decisions. […] Using big data enables managers to decide on the basis of evidence rather than intuition' (5). This statement implies that the more data someone have, the better the decision will be. Therefore, a company should start to collect as much data as possible. 'Size matters, but there are other important attributes of big data, namely data variety and data velocity' (Russom 2011, 6). In addition to large volume, data

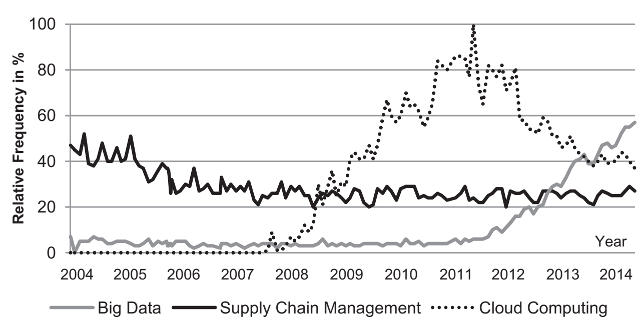


Figure 1. Searches on Google for terms big data, cloud computing and SCM.
Source: Google Trends.

should also be processed as fast as possible in real time and from as many sources as possible in order to support the decision-making process in the best way possible (Brown et al. 2011). In the context of SCM, big data can be seen as an enabler for decision-making and a tool for improving business processes (Cecere 2013). Inspired by Chen, Chiang, and Storey (2012), the following working definition of big data is, therefore, derived: *The big data approach, in general, stands for quickly collecting and analysing large amounts of data from numerous different sources in order to improve business decision-making and overall performance.*

Trying to show how big data can help reduce inefficiencies in the supply chain, this definition fits the purpose of this paper. Furthermore, the definition directly includes the identified three properties (levers) of big data (=3Vs), which will now be viewed in some more detail (Russom 2011, 6; Garg 2013, 5; Hurwitz et al. 2013, 10):

- *Volume (Vo) – A firm's ability to successfully process large amounts of data.* This feature refers to large amounts of data being collected and processed. In businesses, it 'measures the amount of data available to an organisation, which does not necessarily have to own all of it as long as it can access it' (Armour et al. 2013, 996). Therefore, it is not only the size of data collected internally – such as information on inventory levels or order history – that is relevant. External sources can be integrated as well, bringing in new sets of data. In turn, the integration of the external source can increase the volume of data being processed and stored. Consequently, a firm should be able to handle great quantities of information (Garg 2013).
- *Velocity (Ve) – A firm's ability to successfully process data at a high speed.* With improved applications, velocity is also increased. Computer systems do not only deal with large sets of data; they also process information at high speed (Cecere 2013). As Armor et al. (2013, 996) states, 'Data velocity measures the speed of data creation, streaming and aggregation'. Thus, velocity has several possible locations in the processing of data to increase overall speed, allowing users to work with the latest possible sets of data. According to Davenport, Barth, and Bean (2012, 22), 'Companies that learn to take advantage of big data will use real-time information from sensors, radio frequency identification (RFID) and other identifying devices … to respond to changes in the usage patterns as they occur'. This should allow firms to react better and faster to occurrences and develop data-based strategies.
- *Variety (Va) – A firm's ability to successfully integrate various sources of data.* This characteristic refers to the different kinds of sources for data. 'Data variety is a measure of the richness of the data representation, including text, images video, audio, and so on' (Armor et al. 2013, 996). This does not only mean to combine, for instance, data on inventory with information on past demand to plan capacities. In addition, new sources of data can be included, such as web data or RFID chips (c.f. Franks 2012). Furthermore, not only do the different sources introduce variety in big data, they can also differ in form. In this context, Baars and Kemper (2008) researched different solutions on how to deal with structured and unstructured data for the purpose of management support systems.

The characteristics of big data (levers) used in this study are summarised in Table 1.

2.2 *Bullwhip effect*

The bullwhip effect leads to 'excess inventories […], followed by serious inventory shortages; […] excess or insufficient capacity […] unstable production and inefficient production planning and scheduling' (Machuca and Baraja 2004, 210). Significant amount of research has already been done related to the bullwhip effect. One central paper written by Lee, Padmanabhan, and Whang (1997b) sums up major causes, which have been cited and commonly used in later research (c.f. Fransoo and Wouters 2000; Chatfield et al. 2004; Disney, Geary, and Towill 2006; Wu and Katok 2006). The main problems (P) causing bullwhip effects include the following:[2]

- *Demand signal forecasting – Forecasting based on aggregated demand data (P1):* In a supply chain, every member has to plan inventories and orders with the purpose of delivering goods at a certain level of service.

Table 1. Overview of big data levers.

Big data lever	Authors
Volume (Vo): A firm's ability to successfully process large amounts of data	e.g. Hurwitz et al. (2013), Russom (2011)
Velocity (Ve): A firm's ability to successfully process data at a high speed	e.g. Armor et al. (2013), Davenport, Barth, and Bean (2012)
Variety (Va): A firm's ability to successfully integrate various sources of data	e.g. Armor et al. (2013), Baars and Kemper (2008)

Forecasting is often based on the order history from the company's immediate customer (Lee, Padmanabhan, and Whang 1997b, 95). However, those orders do not necessarily represent the immediate needs of a customer. A company's forecast is calculated by using modified numbers. According to Lee, Padmanabhan, and Whang (1997a, 555), 'distortion of demand information arises when the retailer issues orders based on her updated demand forecast'. As the next participant also processes the received information on demand and creates his own forecast, this error is, from that point on, reinforced on every stage of the supply chain.

- *Rationing game – Forecasting based on exaggerated orders (P2)*: When demand outreaches production, buyers are confronted with a situation wherein the seller is not able to deliver the quantity demanded. Therefore, the vendor has to allocate the available resources and capacities to different buyers. Since the buyers anticipate the shortage, they tend to order more than needed, hoping to acquire a bigger portion of the available stock. Houlihan (1987) called this effect 'over ordering' (88). By doing so, the information flow is distorted, making it impossible for the manufacturer to estimate the real demand. Since forecasting often relies on the currently seen demand, the calculated target is based on misleading figures. This results in wrong planning and scheduling.
- *Order batching – Few datapoints on demand information (P3):* Each and every order – such as the transportation or the ordering process itself – causes transaction costs. Since the ambition of any company is to minimise its expenses, one reason for bundling orders can be saving costs (Metters 1997). In accordance to this aim, firms also try to obtain volume or quantity discounts when ordering more of one product at a time (Lee, Padmanabhan, and Whang 1997a). As a result, buyers tend to place orders only at specific points in time, leaving the supplier with no information on the actual demand most of the time. This is the reason why the suppliers' forecasting is based on a smaller set of numbers, making it more difficult to properly forecast future demands and inventories.

The causes of the bullwhip effect, which is summarised in Table 2, have been researched well. Various attempts have also been made to reduce the effect. Some of the earlier approaches used for the reduction will now be analysed (assigned with A).

A central term connected to demand signal forecasting is (A1) *shortening the lead time* (Lee, Padmanabhan, and Whang 1997a, 556). Dejonckheere et al. (2003) have shown that a shorter lead time has a measurable positive impact on the bullwhip effect. This can be done in different ways. For example, trough 'direct marketing […] eliminating channel intermediaries' (Lee, Padmanabhan, and Whang 1997a, 56).

Another possibility to make the flow of information between supply chain members more efficient is to use electronic data interchange (EDI) systems, which grants manufacturers access to the demand data at the retail outlet (Lee, Padmanabhan, and Whang 1997a, 556). This procedure is also known as (A2) *accessing point of sales (POS) information* (Hosoda et al. 2008). Research has shown that EDI systems can significantly improve supply chain performance (c.f. Machuca and Barajas 2004).

The bullwhip effect can also be minimised through vendor managed inventory (VMI). VMI describes a collaborative commerce initiative where suppliers are authorised to manage the buyer's inventory of stock-keeping units (Yao, Evers, and Dresner 2007, 663). With this approach, the buyer does not make ordering decisions by himself anymore. In VMI, distortion of demand information is minimised, stock-out situations are less frequent and inventory-carrying costs are reduced (Çetinka and Lee 2000, 217). Both attempts have focused on (A3) *giving the supplier direct access to information at downstream level*. Additionally, VMI aims at reducing the bullwhip effect by passing the inventory management to the next upstream member (Disney and Towill 2003). In the case of EDI, demand data are transferred electronically.

The main concept to overcome this cause is (A4) *limiting the buyer's flexibility in the ordering process* (Lee, Padmanabhan, and Whang 1997a, 556). The idea is to force the buyer to order amounts that are close to his real needs. This can be done by setting up according to agreements or having some forms of contract to restrict wild open purchase

Table 2. Overview of relevant causes and problems of the bullwhip effect (selection).

Cause (and corresponding problem) of bullwhip effect	Authors
P1: Demand signal forecasting (Forecasting based on aggregated demand data)	e.g. Lee, Padmanabhan, and Whang (1997b); Disney and Towill (2003); Prater, Frazier, and Reyes (2005)
P2: Rationing game (Forecasting based on exaggerated orders)	e.g. Houlihan (1987)
P3: Order batching (Few data-points on demand information)	e.g. Metters (1997); Lee, Padmanabhan, and Whang (1997a)

orders (Souza, Zice, and Chaoyang 2000, 354). The contract assures that all ordered products are actually bought later on. It also improves the quality of the demand data, as it is closer to the actual demand.

As an alternative, Lee, Padmanabhan, and Whang (1997a) also propose the sharing of information with downstream members (556). If the buyers know the production and inventory information about the upstream member, then they could properly adjust their order schedules. However, as the result of a study done by Croson and Donohue (2005) clearly indicates, 'sharing downstream inventory information is more effective at reducing bullwhip behaviour than sharing similar upstream information' (258). Hence, this approach will not be considered in this paper.

Finally, a further attempt is (A5) *lowering the transaction costs of orders*. In consequence, more frequent replenishment is needed in smaller batches, leading to lesser distortion of demand information (Lee, Padmanabhan, and Whang 1997a, 557). This goal can be reached in different ways. For instance, by including third-party logistics providers, economies of scale and economies of scope can reduce the overall costs for transportation (Logan 2000, 24). Introducing computer systems, such as EDI, can increase the efficiency of the involved processes, which, as a direct benefit, will reduce transaction costs (Iacovou, Benbasat, and Dexter 1995, 468).

Table 3 gives an overview of the former approaches used to mitigate the bullwhip effect.

2.3 *Extracting the starting points for big data levers*

Based on the problems of the identified causes (P1–P3) and former approaches (A1–A5), starting points (SP) are formulated. Further, the intensity of the possible impact of big data on the bullwhip effect is examined by fostering supply chain decisions. As noticed, the main problem related to demand signal forecasting is that calculations are based on already aggregated demand data (P1). The former approaches focused on bypassing this issue by either directly granting access to POS information for upstream members (A2) or by directly controlling the downstream inventories of suppliers (A3). An alternative is the utilisation of new sources of information offered by big data (*Va*). Before any customer buys something, some sort of decision has to be made. For instance, earlier research suggests that the possibility to predict an overall demand for cars is likely through the usage of periodically customer surveys (c.f. Curtin 1982). Even though this research is 30 years old and has its limitations, it shows that if it is possible to determine customer sentiment in real time, demand may be forecasted without using order-based data. For instance, Ford Motor, PepsiCo and Southwest Airlines analyse consumer posting about them on social media sites, such as Facebook and Twitter to understand how consumer sentiment about their brands is changing (Bughin, Chui, and Manyika 2010, 8). Even though these companies monitor web data only to analyse marketing success, it is thinkable to improve forecasting techniques by integrating customer sentiment. Based on these insights, the following proposition can be stated as a starting point for big data applications: *The ability to process big data variety (Va) reduces the problems according to demand signal forecasting (P1) and enhances customer sentiment-based forecast accuracy (SP1).*

Another possibility to reduce the bullwhip effect caused by demand signal processing is shortening lead time (A1). According to Liao and Shyu (1991), it generally involves a set of components, which can be matched with a possible big data lever. Some exemplary relations are presented in the Appendix (Table A1). Since *Va* is mentioned primarily, this will be considered the relevant big data lever related to SP2. A second proposition therefore states: *The ability to process big data variety (Va) reduces the problems according to demand signal forecasting (P1) and shortens the lead time in the supply chain (SP2).*

In the case of the rationing game, the identified problem is forecast based on exaggerated orders (P2). One possible reason behind this is the work-around already mentioned by SP1, which is to bypass forecast-based demands and to rely on customer sentiment data. Therefore, this starting point is already covered. Earlier solutions also focused on restricting the buyer's flexibility (A4). This can be considered as an extrinsic motivation, which makes exaggerated ordering impossible. However, this approach did not focus on the recognised root of the problem. Frequently, buyers overstate

Table 3. Overview of former approaches to mitigate the bullwhip effect (selection).

Approach to mitigate the bullwhip effect	Authors
A1: Shortening lead time	e.g. Dejonckheere et al. (2003)
A2: Granting access to POS information	e.g. Hosoda et al. (2008), Machuca and Barajas (2004)
A3: Direct control of downstream inventory	e.g. Disney and Towill (2003)
A4: Restricting the buyer's flexibility	e.g. Souza, Zice, and Chaoyang (2000)
A5: Reducing the transaction costs of orders	e.g. Lee, Padmanabhan, and Whang (1997a), Holland and Sodhi (2004)

Table 4. Overview of starting points for big data analysis.

Affected big data lever	Bullwhip cause (main problem)	Big data starting point
Vo	Rationing game (P2: Forecasting based on exaggerated orders)	SP3: Distribution transparency
Ve	Order batching (P3: Few data points on demand information)	SP4: Order frequency
Va	Demand signal forecasting (P1: Forecasting based on aggregated demand data)	SP1: Lead time
Va	Demand signal forecasting (P1: Forecasting based on aggregated demand data)	SP2: Demand forecast accuracy

orders because they hope to get a bigger part of the available stock. If they knew that this does not help them to get more of the existing products, they would not have had a reason to order more than required. Subsequently, the sellers' process has to allocate resources based on another measure than incoming order size and clearly communicate this procedure. In this context, one example of a possible application of big data is to allocate products in shortage to dealers based on historic sales records (Lee, Padmanabhan, and Whang 1997a, 556). From this point of view, the decision is now based on a large set of historical data (*Vo*) rather than on present orders. The buyers also no longer have an incentive to over order. Based on this, the third proposition states: *The ability to process big data volume (Vo) reduces the problems brought about rationing gaming (P2) while enhancing distribution transparency (SP3).*

While the former causes mainly emerged because of forecasting based on misleading figures, the problem of order batching has been recognised as not having enough data points available on demand information (P3). Former approaches tried to reduce the transaction costs of orders, thereby increasing order frequency and creating more points of data in time (A5). In this case, big data can also be approached this way: Through the use of information technology systems, processing costs can be reduced to a minimum, increasing the processing speed (*Ve*) and letting the customer order smaller batches at a faster pace. A final proposition can then be formulated: *The ability to process big data velocity (Ve) reduces the problems brought about by order batching (P3). It also enhances order frequency (SP4).*

The identified starting points summarised in Table 4 have been rearranged and will be analysed in their historical order of interest (Watson and Marjanovic 2013). After introducing management support systems, data started to grow, which meant that engineers had to deal with its volume. After successfully conquering this problem, the focus shifted towards velocity. Through the introduction of real-time data, processes were getting faster, making the management seek for appropriate solutions to handle the increased speed. The newest difference is the increasing range of data types, such as web data or sensors, resulting in a variety of data sources.

3. Simulation study

By applying the control theory and using the system dynamics approach – a subject introduced by Jay Forrester – the following examinations are performed. It is capable of providing '[…] a common foundation that can be applied wherever we want to understand and influence how things change through time' (Forrester 1991, 5). With the use of system dynamics, it is possible to design processes and simulate outcomes over time. In this research, system dynamics is the basis used to design a common supply chain model. Even more, system dynamics analyses how the model will react to the changes made in the design of demand processing. The basic modelling approach used in this examination is based on the research of Dejonckheere et al. (2003). However, some parts are adjusted for the purpose of this study. Figure 2 provides an overview of the applied control engineering methodology.

As a first step, the real-world problem is analysed (1). Preparation for this step, which is the identification of the different starting points of big data applications, has already been done. Based on the assumed principles, a block diagram model is designed, which represents all earlier made observations (operationalisation of big data) and is the core for the later examinations (2). This diagram now represents the real-world's behaviour in a controlled engineering environment. To see how the system handles inputs and calculates output within a simulation study, the so-called transfer function has to be derived in a subsequent step (3). With this function, it is then possible to compute the estimated output for any randomly chosen input. Rather than one certain type, the reaction of the system to a range of different inputs is of interest, so the transfer function is fed with numerous sinusoidal waves with different frequencies. This procedure is based on the fact that real-life demand data can be seen as comprised of different sinusoids. Feeding the transfer function with a range of sinusoids results in an overview of the systems reaction, which can be summarised using a Bode or frequency response plot. The Bode or frequency response plot represents the amplitude of the generated orders (output)

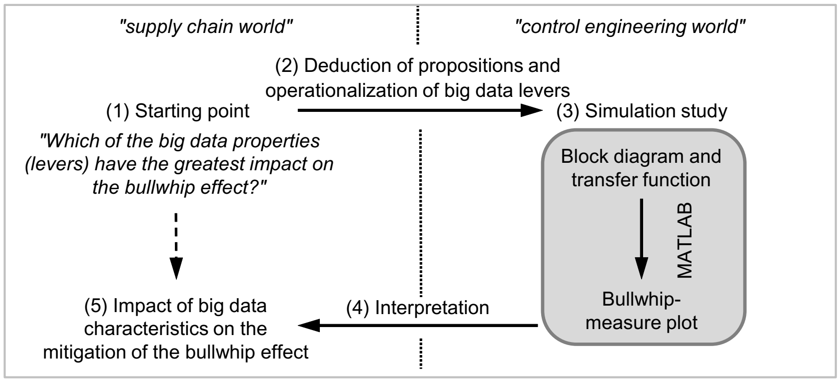


Figure 2. Applied Control Engineering Methodology as a Research Framework.
Source: According to Dejonckheere et al. (2003, 572) and Zhou, Disney, and Towill (2010).

over the amplitude of the sinusoidal demand (input): the amplitude ratio AR (Dejonckheere et al. 2003, 571). The Bode plot curve embodies the definition statement of the bullwhip effect measurement. Thus, the Bode plot can also be used to measure the bullwhip effect. Based on the plots, interpretations regarding big data implications can be drawn (4). Grounded in the analysis and interpretations, practical insights to mitigate the bullwhip effect are obtained (5).

3.1 *Basic model*

The main assumptions made in the basic model simulation include the following: (i) the observed supply chain consists of a single retailer and a single manufacturer, (ii) the manufacturer uses an order-up-to policy and (iii) demand forecasting is based on simple exponential smoothing. The following orders of events are assumed according to the model of Dejonckheere et al. (2003): in each period t, the retailer receives the goods first, then the demand d_t is observed and satisfied. The retailer observes the new inventory level and places an order o_t to the manufacturer. Any unfilled demand is backlogged. The fixed lead time placed at the end of period t is received at the start of period $t+L$. Admittedly, the model applied already covers most aspects concerning the previously identified causes of the bullwhip effect. However, one certain cause is not directly addressed: the rationing game. As companies expect shortages in supply, they order more products than needed and cancel some of those orders later on. This observation can fortunately be transferred into the model, while the demand used for forecasting is higher than the real demand, which will later on be noticed as a change in inventory.

In one direction, the demand goes unmodified directly into the inventory processing. On the other route, before entering the forecasting process of the manufacturer, the demand is altered through a rationing game rate. This rationing game rate is a measure of the intensity of the rationing game taking place. It changes the amplitude of the demand, allowing the manufacturer to consider a higher demand. The rate can theoretically be infinitely high. From those observations, the term $\frac{u}{1-r}$ can be introduced, with u as input and r as the rationing game intensity. The outcome is on a scale between zero and one. To do this, the demand signal going into the forecasting process should be transformed as visualised by the 'black box' in the basic model (Figure 3).

The altered model is justified by making r equal to zero. The generated results equal the ones calculated in the basic model. The measured bullwhip effect should increase as the rationing game rate increases. This can be tested positively. The adjusted MATLAB model is presented in Appendix 2. For further analysis, an initial bullwhip measure result is calculated for the underlying model. A reference bullwhip measure value of 80,248 is determined. This result should make it easier to understand and interpret the impacts of the different starting points discussed in the paper.

The areas of improvements will be analysed separately as follows (Nise 2011, 15):

(1) The starting points (SP) properties are identified in the 'supply chain world';
(2) The SP is transferred into the model in the 'control engineering world' (firstly, each big data lever was separated one by one and, secondly, a combination of the three big data levers);
(3) Block diagrams and corresponding transfer functions are built and bullwhip measure plots are simulated using MATLAB;
(4) The impact of the drawn bullwhip measure plots is interpreted; and
(5) Practical insights to mitigate the bullwhip effect are derived.

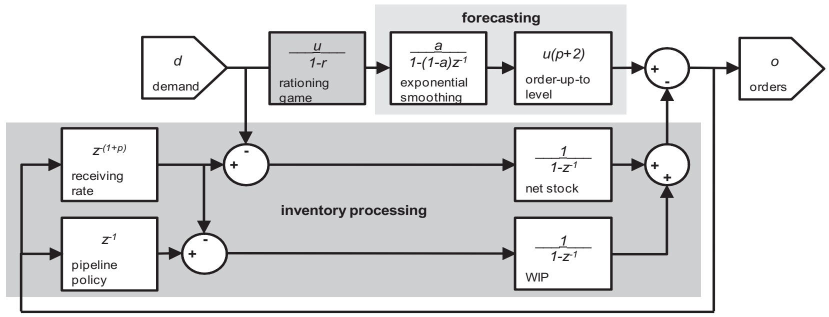


Figure 3. Block diagram of the basic model on the bullwhip effect.

Notations are given below:

d	demand;
u	input of rationing game;
r	rationing game intensity;
a	indirect measure for average age of data;
x	ordered amount of a product over a year;
y	number of orders;
z	amount ordered;
$p+2$	lead time;
o	orders

To transfer the identified starting points into the model analysis, an operationalisation of the big data levers was necessary. To make this possible, a simple 'fuzzy-linguistic approach' was applied (Adamopoulos and Pappis 1996). As the abilities of the big data applications regarding the three *V*'s were manifold and depend on numerous factors, the degrees of maturity were used to express the impact of big data. As Table 5 shows, a fuzzy set is built, transforming linguistic assessments (e.g. very poor to fully applications) into numerical values in an interval of zero to one (Wang and Chuu 2004).

3.2 *Big data starting point 'distribution transparency'*

The starting point of distribution transparency is based on the assumption that firms could allocate goods in relation to historical purchases rather than on present orders by introducing big data into the supply chain decisions. By doing so, buyers would not have an incentive to order goods excessively anymore, thereby reducing exaggerated ordering (P2). The theorem implies that the stronger the use of big data, the more the rationing game can be reduced. The formula

Table 5. Fuzzy linguistic assessment variables of big data used in the simulation study.

Starting point (Area of improvement)	Big data lever	Operationalization terms applied in the basic model	Linguistic variables	Fuzzy numbers
Enhanced distribution transparency	*Vo*	$\frac{u}{1-r(1-Vo)}$	Very poorly applied	(0, *variable*)
			Moderate	0.5
			Fully applied	(*variable*, 1)
Adequate-order frequency	*Ve*	$u(1-Ve)$	Very poorly applied	(0, *variable*)
			Moderate	0.5
			Fully applied	(*variable*, 1)
Shorter lead time	*Va*	$p(1-Va)+2$ and $z^{-(1+p(1-Va))}$	Very poorly applied	(0, *variable*)
			Moderate	0.5
			Fully applied	(*variable*, 1)
Better demand forecast accuracy	*Va*	$(u\ Va)$ and $u(1-Va)$	Very poorly applied	(0, *variable*)
			Moderate	0.5
			Fully applied	(*variable*, 1)

used for the rationing game is $\frac{u}{1-r}$. If no big data is used, the rate should not be affected. If big data is used in a perfect way as implied by the theory, the rate should equal to 1, which means that no transformation has occurred to the demand signal and that if there is, it can be perfectly corrected.

$$\text{Operationalization term: } \frac{u}{1-r} \rightarrow \frac{u}{1-r(1-Vo)} \tag{1}$$

This effect can be operationalised using term (1), in which *Vo* represents a firm's ability to successfully process large amounts of data on a scale from zero (unsuccessful) to one (successful). For the following calculations, a rationing game rate of $r = 0.1$ has been chosen. As expected, the curve (see results for SP 'distribution transparency' in Figure 4) shows a decreasing tendency, showing the positive impact of *Vo*. Measurements to slightly reduce the bullwhip effect are also displayed. The graphic shows that even if used in a perfect way, the starting point can only reduce the bullwhip

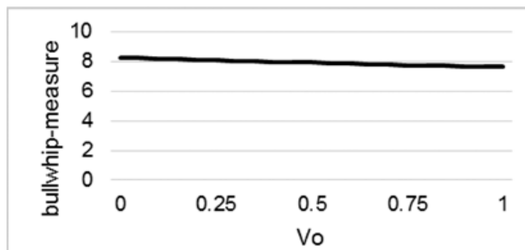
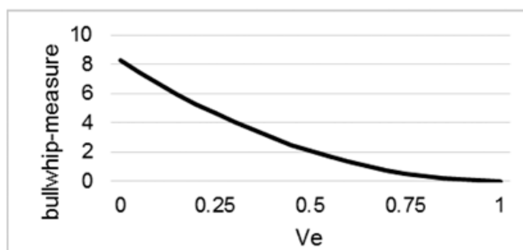
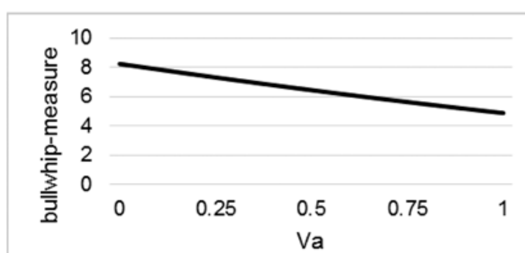
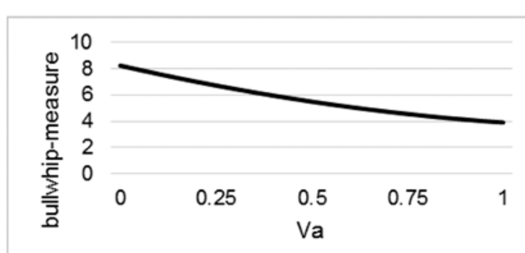
Starting Point	**Big Data Lever**	**Result**
Distribution transparency	*Vo*	
Order frequency	*Ve*	
Lead time	*Va*	
Demand forecast accuracy via customer sentiment	*Va*	

Figure 4. Summary of the big data starting points analysed.

effect back to the level where it was without the rationing game. This shows that the lever can only reduce the additional source of supply chain distractions. It cannot eliminate the effect completely. In this example, a rationing game rate of 0.1 was chosen. However, the impact of this lever is dependent on the size of the rationing game taking place in the supply chain. If the rate is chosen to be higher – for instance, $r = 0.5$ – the impact would be higher because the initial bullwhip measure increases. This fact has to be kept in mind when performing further research on this aspect, considering that the size of the impact is dependent on chosen variables. In further simulations, it was noticed that for any chosen value for *r,* the impact always showed a similar tendency.

3.3 *Big data starting point 'order frequency'*

Processing costs can be reduced to a minimum through the use of information technology systems. In the same manner, processing speed can be increased (*Ve*), allowing the customer to order smaller batches at a faster pace. Mathematically speaking, if x is the ordered amount of a product over a year, y the number of orders and z the amount ordered each time, the following connection would result: $\frac{x}{y} = z$.

Consequently, if y is the number of orders and is increased, then z would be smaller. The effect of *Ve* then leads to more orders with a smaller order size. These two observations now have to be transferred into the model. The signal going into the model, u, is a sinusoidal wave. Its amplitude represents the size of an order. The size of the amplitude has to be linked to a firm's ability to successfully process data at high speed in real time (*Ve*). When multiplying a sinusoidal signal with any number, the amplitude can be altered. To reduce the amplitude of any wave, u has to be multiplied with a number smaller than one, but greater than zero (otherwise no orders would be placed). This can be done using the following formula:

$$\text{Operationalization term: } u \rightarrow u(1 - Ve) \tag{2}$$

The term reduces the amplitude of orders in relation to the corresponding level of *Ve*, which is again running from zero (unsuccessful) to one (successful). If no big data is used ($Ve = 0$), then the signal is not manipulated at all. If big data is used perfectly ($Ve = 1$) and interpreted as if every sold product is directly reported to the next supply chain member, the order size (amplitude) converges towards an infinitely small size. To simplify the previous simulation, only the amplitude was adapted; that is, the mentioned z (amount ordered) is getting smaller, but y (number of orders) is not increased. The result of the simulation states that if the size of orders is reduced, the bullwhip effect is also reduced. However, these insights (see results for SP 'order frequency' in Figure 4) can still suggest a hint to increase order frequency by reducing the order size. It can be seen that increasing the order frequency (or lowering order size) has a high impact on the bullwhip effect. Big data lever velocity can significantly lower the bullwhip measure if applied in a perfect way. This can be explained by the fact that if every sold product is almost instantly reported to the next member in the supply chain, no distraction of demand information can occur because every member directly sees the actual demand at the downstream end of the supply chain.

3.4 *Big data starting point 'lead time'*

The use of big data seems to increase the order frequency. If orders are processed this way, the speed of processing can increase. In turn, the lead time can decrease. In addition, new sources, such as information about traffic or weather, can speed up processes enabling faster shippings (c.f. Waller and Fawcett 2013), making it evitable for firms to include new sources of data into their supply chain planning tools (*Va*). In the basic model, lead time is already included in the variable in the form of $p + 2$. The value of 2 has to be considered as given, as it takes at least one order cycle to deliver and another extra cycle as buffer to keep the service level up (c.f. Dejonckheere et al. 2003). In the end, only p can be influenced. Therefore, two blocks have to be altered. On one hand, p is included in the order-up-to level of the forecasting process. On the other hand, p is also mentioned in the receiving rate, as it can be seen in the following:

$$\text{Operationalization terms: } p + 2 \rightarrow p(1 - Va) + 2 \tag{3a}$$

$$z^{-(1+p)} \rightarrow z^{-(1+p(1-Va))} \tag{3b}$$

A problem for further calculations is that the exponent of the receiving rate is strictly limited to whole numbers due to the properties of the used model. For the purpose of this study, *Va* in the second formula is later on rounded to ensure that the exponent in the simulation always results in whole numbers. The application of diverse information sources for decreasing lead time has a positive impact on the bullwhip effect. The simulation (see results for SP 'lead time' in Figure 4) shows a constant tendency for *Va* to be increased. This means that an increase in the level of *Va* has a proportional impact on the bullwhip measure. Even though the second black box – the receiving rate – was only capable of working with whole numbers, the curve surprisingly still shows a very smooth tendency. The delay time was thereby truncated. Contrary to initial thoughts, no abrupt change or step-like patterns can be observed. This may be an indication that the size of the lead time in inventory processing does not have a great impact overall. Nevertheless, lowering the lead time cannot fully reduce the bullwhip measure. Even if *Va* is perfectly applied, the measure for the chosen environment can only be reduced by about a half. One possible explanation for this result is that in the model, the lead time $p+2$ cannot be smaller than two. Therefore, even if it is possible to reduce some components of lead time, such as order preparation, order transit to the supplier, supplier lead time and preparation time for availability, in the end, it still takes time to physically deliver products.

3.5 *Big data starting point 'demand forecast accuracy'*

The starting point 'demand forecast accuracy' is based on the assumption that the development of customer sentiment and demand will have a similar shape over time. However, it takes time until customer sentiment is transformed into real demand (c.f. Curtin 1982). Therefore, the development of future demand can be better predicted if it is possible to measure customer sentiment such as in monitoring social media channels. In this case, a system has to be set up, wherein forecasting will be based on customer sentiment rather than on order data from customers (resulting in a higher demand forecast accuracy). A first enhancement was introduced to transfer this assumption into the model. The so-called demand realisation with a value of z^{-1} modifies the flow of demand information. This is implemented in a way that processed information is held back for a certain period (in this case, one period). This alteration can also be called delay because the information that is passed gets delayed. This simulates the idea that it takes time for customer sentiment to be transformed into real demand. The operationalisation of 'demand forecast accuracy' was done with the following new blocks:

$$\text{Operationalisation terms: } (uVa) \tag{4a}$$

$$u \to u(1 - Va) \tag{4b}$$

Both terms refer to customer sentiment. When the value of *Va* is increased, meaning the better the big data lever of variety is applied, the more the forecasting process can be done based on customer sentiment data. On the other hand, an increase in *Va* decreases the relevance of information coming from the registered demand, making forecasting less dependent on the order behaviour of immediate customers. A side effect can already be seen in the model. While the demand in the form of orders is modified by the rationing game, the direct processing of customer sentiment data bypasses this step. The starting point that was last tested also seemed to have a positive impact on the bullwhip measure (see results for SP 'demand forecast accuracy via customer sentiment' in Figure 4). The more forecasting changes its underlying information source has to customer sentiment data, the less bullwhip effect can be measured. However, even with a perfect application of the big data lever *Va*, the bullwhip effect cannot be fully reduced. Also interesting is that the shape of the curve has a tendency to bend slightly. This means that during the first stage, big data lever variety has a higher proportional impact than when it was developed.

In Figure 4, an overview of the analysed SPs and corresponding big data levers is shown with the result of the simulation along with the initial setting chosen.

3.6 *Combination of big data levers*

All former starting points are combined in one model (Figure 5). This allows the analysis of the behaviour of the model in the different combinations of levels of the big data levers. It also allows the possibility to directly see which levers have a higher impact on the bullwhip measure.

For the simulation, the model was fed with all possible combinations of values for the different big data levers, running from zero to one with a step size of 0.2. The result is plotted in a three-dimensional coordinate system with *Ve* on the *x*-axis, *Va* on the *y*-axis and *Vo* on the *z*-axis (see Figure 6). The resulting bullwhip measure for each point in the cube is represented by the size of the corresponding circle. Summing up all former insights of the analyses, the figure combines all different big data levers. It can be seen that in relative perspective, the big data lever *Ve* has the biggest potential to reduce the bullwhip measure.

The next source that potentially reduces the bullwhip effect is the big data lever *Va*. Going through the data along the *y*-axis, an impact on the size of the circle can be seen. In comparison to the reduction through *Ve,* this impact is not

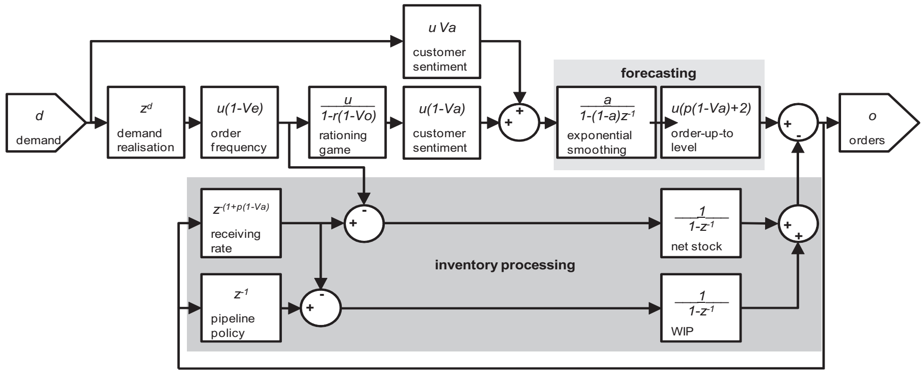


Figure 5. Block diagram of the simulation model with a combination of all big data levers.

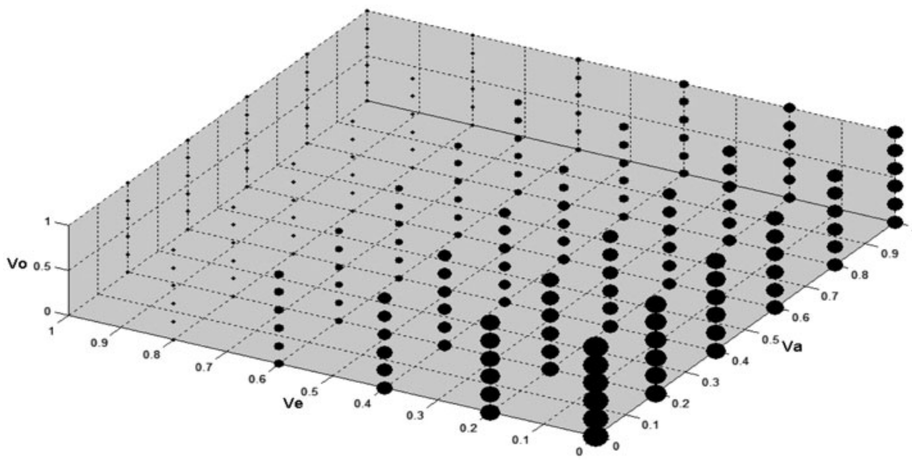


Figure 6. Result of simulation with big data lever combinations.

as strong. The impact of the last big data lever *Vo* cannot be visually noticed in this illustration as the relative effect is too small. In this context, the meaning of the bullwhip measure has to be further analysed. The bullwhip measure is defined as the area beneath the Bode plot curve, which represents the ratio $\frac{\text{Var order}}{\text{Var demand}}$ for the different frequencies of the ingoing sinusoids (Lee, Padmanabhan, and Whang 1997a). As long as the ratio is greater than one, the variance of the processed signal is amplified upstream of the channel. However, it can also happen that the resulting output falls beneath one, which indicates a decrease in the variance of the processed demand signal (c.f. Dejonckheere et al. 2003). In other words, not only can the variance amplification be reduced; the processed signal is smoothed upstream as well. Since the bullwhip measure does not allow a look into the shape of the underlying Bode plots, it cannot completely be stated which exact measure size represents a smoothing effect. Nevertheless, a smaller number still means less bullwhip effect and can even be considered as a smoothing effect.

In addition, the demonstrated potential of *Ve* has to be critically scrutinised further. As *Ve* is increased, the size of orders decreases and the number of orders increases. In the simulation, the size of orders theoretically reached almost zero. Since this scenario is unrealistic due to the standardised sizes of shipment or distribution packages, this observation can probably not be transferred directly into real-world SCM. There is also the question on whether order sizes can become more costly than the saved expenses of the reduced bullwhip effect in the end. Therefore, the real potential of *Ve* is most likely smaller compared to the supposed potential of the simulated results.

To complete the analysis, the impact of the big data levers, in relation to the different underlying sets of data, will now be further analysed.

3.7 *Robustness analysis*

In the previous analyses, variables describing and influencing the simulation were fixed at a certain level. This part illustrates the impact of the chosen variables. These variables are *a* (indirect measure for average age of data), *p* (lead time),

Table 6. Further big data settings and the resulting bullwhip measure (altered input variables highlighted).

Focus	Simulation setting chosen (input data)				Bullwhip effect for the chosen value of big data levers (output data)					
	A	*p*	*d*	*r*	0	0.2	0.4	0.6	0.8	1
a	0	3	1	0.1	3.1	2.0	1.2	0.5	0.2	0.0
	0.1111	3	1	0.1	8.2	4.1	1.9	0.8	0.3	0.2
	0.2222	3	1	0.1	16.1	6.9	2.8	1.3	0.8	0.7
	0.3333	3	1	0.1	27.4	10.6	4.0	2.0	1.7	1.7
	0.4444	3	1	0.1	42.6	15.1	5.4	3.1	3.1	3.2
p	0.1111	1	1	0.1	5.9	3.2	1.6	0.7	0.3	0.2
	0.1111	2	1	0.1	7.0	3.7	1.7	0.7	0.3	0.2
	0.1111	3	1	0.1	8.2	4.1	1.9	0.8	0.3	0.2
	0.1111	4	1	0.1	9.6	4.6	2.0	0.9	0.4	0.2
	0.1111	5	1	0.1	11.0	5.1	2.2	0.9	0.4	0.2
d	0.1111	3	1	0.1	8.2	4.1	1.9	0.8	0.3	0.2
	0.1111	3	2	0.1	8.2	4.0	1.8	0.8	0.3	0.2
	0.1111	3	3	0.1	8.2	4.1	1.9	0.8	0.3	0.2
	0.1111	3	4	0.1	8.2	4.1	1.8	0.8	0.3	0.2
	0.1111	3	5	0.1	8.2	4.1	1.9	0.8	0.3	0.2
r	0.1111	3	1	0.0	7.6	3.9	1.8	0.8	0.3	0.2
	0.1111	3	1	0.1	8.2	4.1	1.9	0.8	0.3	0.2
	0.1111	3	1	0.2	9.1	4.3	1.9	0.8	0.3	0.2
	0.1111	3	1	0.3	10.2	4.6	2.0	0.8	0.3	0.2
	0.1111	3	1	0.4	11.7	5.0	2.1	0.8	0.3	0.2

d (demand) and *r* (rationing game rate). The first two variables were already included in the model of Dejonckheere et al. (2003), while the second two have been introduced in this study. The meaning of variable *a* has been mentioned specifically because it indirectly represents the average age of the data, which is defined as $\frac{(1-a)}{a}$. An increase in *a* is interpreted as a decrease in the average age of the data. The model now combines all four SPs in a *ceteris paribus* approach. The model is then fed with different settings of *a, p, d* and *r*. Moreover, different levels for the big data levers are chosen. On this basis, the simulation calculates the bullwhip measure. This procedure is then repeated for the other set of variables.

Results are summarised in Table 6. It can be noticed that only a change in *a* weakens the impact of perfectly applied big data. All other variables at this stage were not able to influence the result, which means that the chosen variables will not weaken the impact of big data. However, this is not true for the case where no big data is used at all. In this column, a change results in the measured bullwhip effect.

An exception to this observation is *d*. Somehow, altering this parameter only shows small, insignificant changes. This means that if customer sentiment gets accurately measured, how long it takes until the sentiment is transformed into actual demand does not really make a difference. However, this result shows a weakness of the model. It assumes that customer sentiment can be perfectly measured and will, afterwards, be exactly transformed into real demand as measured before. In reality, this probably will not be the case.

4. Implications

The simulation study shows that the support systems of supply chain decisions should primarily focus on applying the big data lever of velocity. This means that data should be captured, processed and transferred as fast as possible. Not only should this be applied for data within a particular firm, further it should also be applied amongst supply chain members (inter-organizationally). As the results of the simulations suggest, the bullwhip effect can be strongly reduced. Some implications can be derived out for the supply chain executive:

- *Big data velocity and SCM.* The importance of agility and speed in decision-making in the context of SCM is undisputed. The currentness of data has always been a crucial factor gaining even higher importance in the supply chain context. First of all, the research has shown that the big data property of velocity offers the biggest opportunity to increase the efficiency of the processes in the supply chain. Assuming a multi-level supply chain, these characteristics become even more important for the last member upstream. As the number of intermediaries increase, the longer it takes for information to reach the last member in the channel. Multistage supply chains can

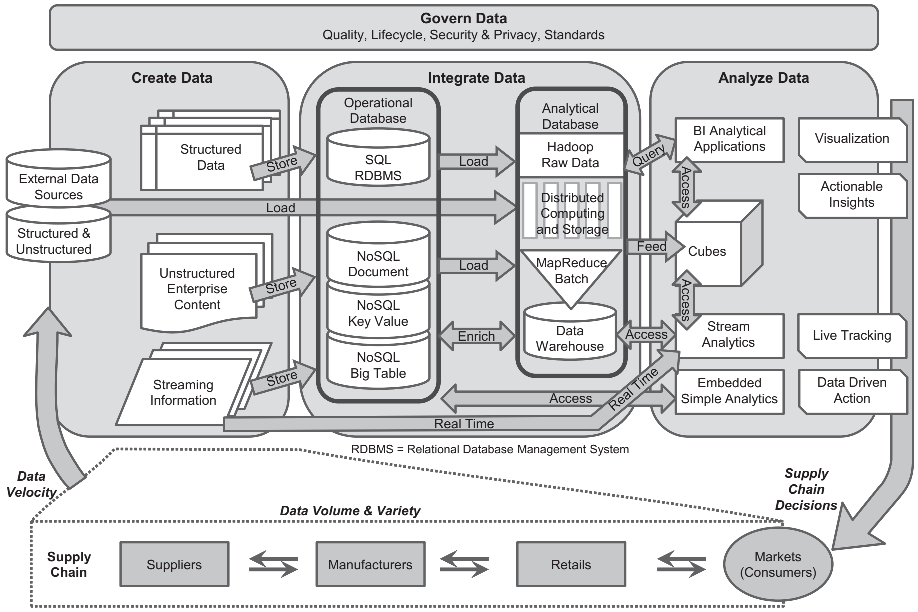


Figure 7. Big data application for SCM (schematically).

profit even more by introducing big data applications to increase processing speed. They have multiple potential compared to two-staged supply chains.

- *Big data variety and SCM.* One reason for the massive rise in data volume in the supply chains is the fact that most of the important data sources are relatively new. New technologies, such as social networks, RFID tags and smartphones produce amounts of semi-structured and unstructured sources, for instance audio, video, webpage and text data. Since numerous members are involved in the process, significant amount of data is generated while processing goods. By harvesting all of this data sources and combining them, advances in order handling can be made. One of the greatest challenges in the field of big data is to find new ways for storing and processing the different types of data, as the old databases are mainly structured for only one type of data (Chen, Mao, and Liu 2014).
- *Big data volume and SCM.* The last lever – volume – however, may also be of bigger interest for multistaged supply chains than to two-staged supply chains, as more data are involved in the process. Supply chain executives should take this into account. However, the increase in data volume pulls the result that much of the data-sets are not complete (problem of missing volumes). This could be because the data is running across multiple systems (Balaraj 2013).

Traditional applications have not been able to fully support the mitigation of the bullwhip effect (Narayanan, Marucheck, and Handfield 2009). The challenge with those supply chain applications is that they often cope with transactional data only (e.g. out of an Enterprise Resource Planning system). According to Balaraj (2013), such applications will become more and more obsolete in the future, as they may not be able to handle the increasing volume, velocity and variety of the data generated by various new sources. By causing unexpected changes in the ordering quantities, the bullwhip effect demands system flexibility on both the side of companies and applications. Traditional DSSs are often too rigid to react fast enough to unplanned supply chain events. Therefore, it is not primarily the data that is lacking so far, but the appropriate approaches that can be used to convert the enormous amounts of raw data into formats that can be leveraged to support decisions (Balaraj 2013). As the implementation of big data applications can provide the lacking DSSs, big data, as a technological driver, might bear great potential for (a) increasing speed in decision-making in general and (b) building up agility in supply chains in particular (Christopher 2000).

5. Conclusion

5.1 *Contributions*

This research has shown how big data levers can reduce the bullwhip effect and which of them has the biggest potential to do so. Possible starting points for big data were identified and their potential was tested using a simple two-staged supply chain model. Results showed that the big data lever 'velocity' has the greatest impact on the bullwhip effect. These outcomes are in accordance with comparable results published by Dejonckheere et al. (2004) on the impact of information enrichment on the bullwhip effect in the supply chains.

The data properties 'volume' and 'variety' have less vigorous effects. In the exemplary model calculation, it was shown that already a 'moderate' utilisation level of the velocity ($Ve = 0.5$) causes a fourfold reduction of the bullwhip effect. *Vo* and *Va* have not even a similar effect: the bullwhip effect could only be halved. Therefore, any solution approaches should be focused on 'speed' and the reduction of the 'order processing time'. Like Figure 7 shows, structured and unstructured data should be gathered along the supply chain, integrated and analysed preferably in real time. On basis of the IT-enabled triad 'create data', 'integrate data' and 'analyse data', supply chain solutions can be improved.

Regardless of its overall potential, however, big data will neither serve as a silver bullet to fulfil the 'dream of integration' nor will it entirely eliminate the causes or symptoms of the bullwhip effect. Even though new technologies and applications can help integrate large, disparate sets of data in lesser time, companies involved in the supply chain need to be willing to share this data and interact with each other in a collaborative manner.

5.2 *Limitations*

In the course of this study, the main focus was laid on the positive effects that can be generated by big data applications in the context of SCM. The multifaceted challenges that go hand-in-hand with the development, implementation and management of business-value-generating big data strategies cannot be discussed in more depth. To derive a concluding statement about the potential of big data applications in SCM, further research should be done to address those challenges. Another limitation lays in the relative novelty of the topic on *big data* itself. This circumstance made it difficult currently to find high-quality scientific contributions or even empirical evidences of big data implementations in general, especially in the context of SCM. As a result, empirical data about the full potential of big data in the context of the bullwhip effect are not available so far. Hence, the impact of the different facets of big data on the bullwhip effect had to be modelled based on qualitative assumptions.

5.3 *Future research*

One basic point of improvement for other studies is to expand the introduced model of a two-staged supply chain into more stages or even multi-production systems (Potter et al. 2009). On the one hand, this simplification made it easier to bring in the big data levers. On the other hand, it is not possible to judge their impact in a multistaged environment in full extent. Furthermore, the analyses should be repeated along various bullwhip models with advanced forecasting methods (e.g. Gaalman and Disney 2009; Ma et al. 2013; Li, Disney, and Gaalman 2014). This study also analysed the impact of big data on the variance of demand. Nonetheless, it did not cover the involved costs (especially the costs to implement and drive a big data application) and capabilities. It may even be that investing in improved big data levers is more costly and challenging than the downsides of other approaches. In addition, it would be interesting to examine other approaches on the bullwhip effect with the same model to be able to directly relate the results with each other. This might be able to provide comparable results and produce more details about the different approaches.

Furthermore, an in-depth comparison to other internet technology (IT)-enabled mitigation approaches of the bullwhip effect should be conducted. Apart from EDI and VMI (Waller, Johnson, and Davis 1999), further strategies, such as Efficient Consumer Response, Quick Response and Continuous Replenishment Programmes (Raghunathan and Yeh 2001) can be discussed and compared to big data applications. Consequently, additional touch points and synergies between these different approaches can be derived. Finally, future research should clearly discuss and empirically demonstrate how big data analytics helps to reduce standard deviations (variance of demand) and the signalling factor in forecasting.

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Disclosure statement

No potential conflict of interest was reported by the author.

Notes

1. It shall be noted here that the terms ‘big data’, ‘big data analytics’ and ‘big data applications/solutions’ have different meanings. ‘Big data’ itself refer to the ‘3 Vs’ (volume, velocity and variety); these data properties are called ‘big data levers’. ‘Big data analytics’ stand for different techniques, like ‘predictive analytics’, ‘monitoring analytics’, ‘exploratory analytics’ and ‘classification analytics’ (Manyika et al. 2011). Single ‘big data applications’ or more comprehensive ‘big data solutions’ refer both to all software- and hardware-related means – in terms of technologies – that help to aggregate, manipulate, manage or even analyse large sets of data (‘big data’) to discover patterns and other useful information (e.g. Taylor 2011).
2. A further problem arises with ‘price variations’. By often stimulating demand for their products through seasonal discounts or rebates, companies cause this last source of the bullwhip effect, which therefore is also called promotion effect (Disney and Towill 2003). Even though the real cause of the problem has another source, in the end, the underlying problem is very similar to P1. Therefore, ‘price variations’ will not be reported separately for the further examinations in this study.

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Appendix 1. Relations between big data and lead time components

Table A1. Exemplary relations between big data levers and lead time components.

Lead time component	Big data lever: reasons
Order preparation	*Va*: ‘E-replenishment saves time and money by replacing paper catalogues/drawings and manual activities with electronic catalogues/drawings, …’ (Robinson, Sahin, and Gao 2005, 34)
Order transit to the supplier	*Ve*: Computer systems speed up transactions (c.f. Scala and McGrath 1993, 87)
Supplier lead time	*Va*: ‘RFID could automatically check that all items from the bill of material are in place’ (Rutner, Waller, and Mentzer 2004, 37)
Items transit time from the supplier	*Va*: ‘Optimal routing, taking into account weather, traffic congestion, and driver characteristics’ (Waller and Fawcett 2013, 82)
Preparation time for availability	*Va*: ‘RFID could input exact counts of incoming items into the warehouse management system’ (Rutner, Waller, and Mentzer 2004, 37)

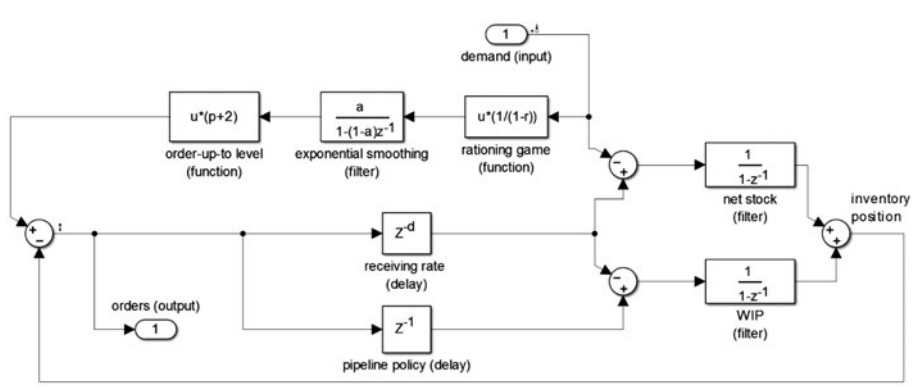

Figure A1. Adjusted basic MATLAB model.

Appendix 2. Verification of the adjusted simulation model

Table A2. Calculations to verify adjusted model.

	Original model	Adjusted model	Rationing game rate

Formula	a = 0.1111;
	p = 3;
	io = getlinio('mod_s');
	linsys = linearise('mod_s',io);
	bode(linsys)
		a = 0.1111;
		p = 3;
		r = 0;
		io = getlinio('mod_s0');
		linsys = linearise('mod_s0',io);
		bode(linsys)
			io = getlinio('mod_s0');
			p = 3;
			a = 0.1111;
			r = 0;
			q = pi/100;
			w = linspace(0,20,100);
			stepsize = 0.05;
			stepamount = ((1/stepsize)+1);
			x = zeros(1,stepamount);
			y = zeros(1,stepamount);
			period = 1
			stop = 1 + stepsize;
			while (r < stop)
			linsys = linearise('mod_s0',io);
			mag = bode(linsys,w);
			mag(:,:,1) = 1;
			G = power(mag,2);
			g = sum(G);
			S = g * q;
			x(period) = r;
			y(period) = S;
			r = r + stepsize;
			period = period + 1
			end

Result