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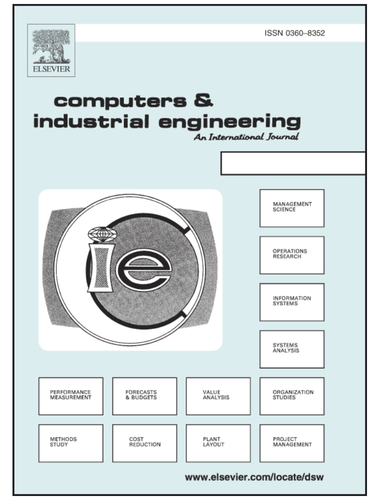

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Niels Bugerta, Rainer Lascha

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Effectiveness of Responsive Pricing in the Face of Supply Chain Disruptions

Niels Bugert[a], Rainer Lasch[a],

[a]*Chair of Business Management, esp. Logistics, TU Dresden, Germany*

Abstract

Disruptions of the material flow can cause serious financial damage for supply chain partners to the extent of even jeopardizing their survival. To cope with this hazard, several proactive and reactive mitigation strategies have been suggested in the research literature of supply chain risk management. To our knowledge, only back-up supply and structural changes of the information flow have been incorporated by network level simulation models. Moreover, a detailed assessment of the disruption length's effect on the resulting costs of a disruption is still missing. We have conducted a simulation study with system dynamics, split into three simulation experiments, to quantify the disruption costs subject to various disruption lengths and to evaluate the effectiveness of responsive pricing regarding the costs saved as well as the order fulfillment rate. We have analyzed the height of the price change and the operating time of this reactive strategy to be able to provide insights into the general behavior of the system and the strategy. For this purpose and since no real supply chain data has been available, we have extended the approach of Wilson (2007) to a two-product model with monetary parameters. A uniform space-filling approach combined with Kriging interpolation has been selected to create response surfaces for two of our three research questions. Our study reveals that there is a disproportionate influence of the disruption length on the overall disruption costs. In our model, the effect of the height of the price change is significant. The ideal height of price change initially increases for longer disruptions until an optimum range is reached. The operating time of the price change has a smaller effect on the effectiveness. Despite the fact that the effectiveness can be further optimized by considering the operating time, our study indicates that near-optimum results can be obtained by having responsive pricing in effect for the acute time span of the disruption.

Keywords: Supply Chain Disruptions, Responsive Pricing, Supply Chain Risk Management, System Dynamics

1. Introduction

Supply chain disruptions are considered to be a combination of an unforeseen triggering event and the resulting consequences which jeopardize the flow of material and normal business activities significantly (Wagner and Bode, 2006). Well documented examples of costly supply chain disruptions have been the fire at a Phillips semiconductor plant in 2000, Hurricane Mitch's catastrophic damage to banana production in Central America in 1998, and the 1999 earthquake in Taiwan, which caused the spot price of memory chips to increase by a factor of five (Chopra and Sodhi, 2004; Norrman and Janson, 2004; Latour, 2001; Griffy-Brown, 2003; Papadakis, 2006). In 2011, an earthquake off the northeastern coast of Japan caused major disruptions in multiple supply chains due to a combination of earthquake damages, flooding by the resulting tsunami, and the radiation exposure in consequence of core meltdowns of the Fukushima Daiichi nuclear power plant stemming from the damaged water cooling system (Tabuchi, 2011; Srinivasan and Rethinaraj, 2013). Japan's gross domestic product dropped by 2.1% in the second quarter of 2011 and exports by 8% (Fujita and Hamaguchi, 2012). Direct economic losses due to these events have been estimated around \$340 billion (Srinivasan and Rethinaraj, 2013; Chakravarty, 2013). Toyota, as one of the many effected automotive manufacturers, experienced immediate out-of-stock events for over 400 parts and a reduction of production capacity for the following six months (Tabuchi, 2011; Norio et al., 2011). Hendricks and Singhal (2005) have detected an increase in the number of reported disruptions between 1989 and 2000 and empirically identified drastic immediate and long-term effects for the associated company's stock value and equity risks. The perceptible trend towards outsourcing, increasing business cooperation, and lean management initiatives, such as just-in-time concepts and the reduction of inventory, is believed to lead to higher risk exposures for supply chain partners combined with greater repercussions for the whole network in case of an eventual disruptive trigger (Kleindorfer and Saad, 2005; Stecke and Kumar, 2009).

This focus on designing lean and efficient, yet more vulnerable, supply chains motivates the output of research in the field of supply chain risk management (SCRM), which aims to identify, analyze, and reduce the risks for the entire supply chain through a systematic and collaborative approach amongst all supply chain members (Thun and Hoenig, 2011; Goh et al., 2007; Jüttner, 2005). SCRM strives to take reasonable proactive and/or reactive measures in order to decrease vulnerability as well as to increase resilience and/or robustness of the supply chain (Waters, 2011; Kleindorfer and Saad, 2005). Whereas the concept of vulnerability describes the susceptibility of the supply chain to specific or unspecific risk events, resilience is regarded as the system's ability to quickly return to a stable state after experiencing disturbances (Colicchia and Strozzi, 2012; Heckmann et al., 2015; Waters, 2011). In contrast to resilience, the concept of robustness focuses on using some form of redundancy to safeguard the system's reliability without the support of reactive measures to stabilize the disrupted system (Kleindorfer and Saad, 2005). A variety of mitigation strategies have been developed and discussed, which range from basic, abstract approaches, such as risk avoidance and risk acceptance, to more tangible references, such as the deployment of cross-trained employees, process postponement, and silent product rollovers (Zsidisin and Ritchie, 2009; Sodhi et al., 2012; Rajesh et al., 2014). One popular, oft-quoted example of a recommended mitigation strategy has proven to be an efficient and successful reactive countermeasure against supply chain disruptions in practice: Dell's responsive pricing strategy in 1999 (Tang, 2006; Sodhi and Tang, 2012; Tomlin, 2006; Lee, 2004). After an earthquake hit Taiwan and damaged an industrial park with 28 semiconductor fabrication facilities responsible for 10% of the world consumption of computer memory chips and more than two-thirds of the worldwide production of computer motherboards, Apple and Dell were affected for weeks and used different reactive strategies to cope with this disruption (Papadakis, 2006; Lee, 2004). While Apple attempted to convince customers to accept slower versions of the affected computers and was subsequently inundated with customer complaints, Dell offered special price incentives to shift customer demand to unimpaired computer models. Due to its flexibility, Dell was able to actually improve its earnings in 1999 by 41% and gained market shares in the earthquake's aftermath (Tang, 2006; Lee 2004).

Since, to our knowledge, responsive pricing has not been analyzed with a network-level simulation model, we use a system dynamics approach to assess the advantages as well as disadvantages of responsive pricing quantitatively in a multi-tier, two-product supply chain which faces disruptions ranging from 0.1 to 20 days. We measure the effectiveness of responsive pricing by conducting a simulation study and comparing various heights and durations of price variations with each other as well as with the basic case of having no reactive strategy in place.

System dynamics has been chosen for this paper's aim because it is capable of reflecting the dynamic and interdependent nature of a supply chain on a high level of abstraction while maintaining a manageable modeling effort. Furthermore, this technique is suitable for What-If analyses and fits well with the characteristics of supply chain disruption risks, which, in contrast to operational risks, generally possess low probabilities of occurrence combined with dramatic consequences (Kleindorfer and Saad, 2005; Knemeyer et al., 2009).

The rest of this paper is structured as follows. A brief literature review on simulation models concerning disruptions and disruption risk on a network level comprises the content of the subsequent section. Section 3 outlines our research methodology, states our research questions, and describes our Design of Experiments. The fourth section describes our system dynamics model. It specifies our assumptions regarding the characteristics of the modeled disruption, the structure and basic behavior of our model, and our parameter specifications. Section 5 presents our findings and discusses the results of our simulation experiments. The last section contains a conclusion, a discussion of this paper's limitations, and a brief outlook for future research possibilities.

2. Literature review

The early evolutionary stages of scientific contributions to SCRM consist predominantly of conceptual research. Over the last century, however, an increase in the use of quantitative decision support tools can be detected (Tang and Musa, 2011). A general overview on conceptual work and quantitative approaches can be found in Ho et al. (2015). For a review on quantitative models structured by supply chain planning problems, we refer to Tang (2006). The majority of quantitative approaches consist of deterministic and stochastic optimization models of supply chain planning problems, such as supplier selection and supply chain design under the influence of parameter uncertainty. As analytical models struggle with optimizing highly complex and dynamic systems, such as modern globalized supply chains, numerous researchers call for quantitative models integrating uncertain, complex, propagative, and dynamic aspects on a network level (Persson, 2011; Hennies et al., 2014; Almeder et al., 2009; Ghadge et al., 2012; Colicchia and Strozzi, 2012; Oehmen et al., 2009). Despite being under-represented, multiple quantitative modeling approaches that focus on supply chain disruption risks have been developed by using techniques like Petri-Nets (PN), System Dynamics (SD), Discrete Event Simulation (DES), Agent-based Modeling, and Bayesian Belief Networks (BN).[1]

Wu et al. (2007) apply a PN to model the propagation of a disruption with respect to changes in cost and lead time in a four-tier supply chain. Zegordi and Davarzani (2012) extend the model of Wu et al. (2007) by incorporating multiple disruptions and their interdependencies. Blackhurst et al. (2008) use a PN-model to calculate non-reachable states within the supply chain system, which are considered to be causes of potential disruptions. John and Prasad (2012) extend the model of Blackhurst et al. (2008) by using a colored PN for conflict detection. Tuncel and Alpan (2010) identify disruption risks through a failure mode, effects and criticality analysis (FMECA) and use a PN to model a supply chain including three of the identified risks. Simulation is subsequently used to quantify the effectiveness of combinations of three mitigation strategies, which are assumed to lower the risk's probability of occurrence while incurring certain cost, by evaluating the total revenue and customer order fill rate. Blos and Miyagi (2015) describe Inoperability Input-output Modeling (IIM) with a PN approach to model the interdependent effects of one or more disruptions on performance metrics like cost and lead time. IIM originally stems from Leontief's Input-output Model and attempts to foresee the resulting economic losses and inoper-

[1] For a short review of some simulation techniques used in supply chain management, we refer to Kleijnen (2005).

ability suffered by different interdependent industry sectors (Leontief, 1951; Santos and Haimes, 2004). Wilson (2007) uses SD to examine the effect of transportation disruptions on a five-echelon supply chain with fixed transit times and compares a traditional supply chain to a supply chain coordinated by a vendor managed inventory system. In a similar approach, Sidola et al. (2011) compare the effects of two transportation disruptions on a regular supply chain to a so-called visible four-tier supply chain in which all demand information is shared between partners. Bueno-Solano et al. (2014) simulate the impact of a border shut-down on the inventory levels and inventory costs of a four-tier supply chain due to a terrorist attack. The same SD model was used by Cedillo-Campos et al. (2014), who study the impact of criminal acts on the inventory performance and total costs of a four-tier supply chain located in South America. Wang et al. (2014) analyze the effectiveness of using a contingent supplier or a standby supplier in case a disruption occurs in a two-tier supply chain. Li et al. (2016) study the effect of 13 risk events and two mitigation strategies (increasing transportation equipment capacity and increasing the amount of transport vehicles) on the performance of a chemical supply chain transportation system impaired by 13 operative and disruptive risks. Badurdeen et al. (2014) use a BN to study risk interdependencies of a supply chain consisting of 11 suppliers, one focal OEM, and 20 customers. Garvey et al. (2015) model the propagation of disruption risks by using a BN and specifically developed propagation measures. Qazi et al. (2015) analyze the effects of multiple mitigation strategies, which reduce the probability of occurrence at the expense of individual mitigation costs, on the expected loss in the supply chain system. Agent-based Modeling has been used by Park (2014) to study the behavior of a three-tier supply chain with two different products in different disruptive scenarios. The customer behavior of this approach has been modeled with the use of SD. In a similar Agent-based Modeling approach, Seck et al. (2015) study the effect of different scenarios (demand forecast accuracies and presence of disruption) in a three-tier supply chain. Schmitt and Singh (2009; 2012) combine Monte Carlo Simulation with DES to calculate the effects of different disruptive scenarios in combination with the mitigation strategy of backup capacity at different locations on the performance measures of a three-tier supply chain. Hishamuddin et al. (2015) compare the impact of two different disruption types (supply disruption and transportation disruption) on the total recovery costs of a three-tier supply chain. The approach of Aqlan and Lam (2016) combines a goal programming approach and a DES model to find the best mitigation strategies, inventory levels, and production quantities under budget constraints in a three-tier supply chain. Risk mitigation is incorporated by lowering the probabilities of occurrence.

Out of the presented approaches, eight models incorporate mitigation strategies so far. While the approaches of Wilson (2007), Sidola et al. (2011), and Wang et al. (2014) compare different structures of the supply chain (information sharing, backup supply), other approaches like Tuncel and Alpan (2010), Aqlan and Lam (2016), and Qazi et al. (2015) incorporate mitigation strategies by lowering the probabilities of occurrence. The approaches of Li et al. (2016) as well as Schmitt and Singh (2009; 2012) change parameters such as the transportation capacity and study their effect on the system. A detailed analysis of responsive pricing as a mitigation strategy is still missing. Furthermore, a thorough quantification of disruption costs has not been tackled up until now. We want to fill this gap by conducting a simulation study based on SD.

3. Research methodology

A SD simulation experiment is considered to be reasonable for the modeling of supply chain disruptions (Sidola et al., 2011; Cedillo-Campos et al., 2014; Wang et al., 2014). Therefore, we chose SD for the assessment of different pricing strategies. A simulation experiment consists of a single test or a series of simulation tests in which input variables are purposefully changed and the output response is observed to gain insight into the behavior of a system (Montgomery, 2012; Sanchez, 2005). Pre-experimental planning, namely the definition of research goals, the choice of factors, levels, and ranges, and the selection of response variables, is considered to be of importance, as it influences the choice of the experimental design (Montgomery, 2012; Kleijnen, 2005). Our research questions (RQs) are defined as follows:

- RQ 1: What are the monetary consequences of disruptions of different lengths for supply chain partners which do not have any mitigation strategies in place?
- RQ 2: How does the height of the price change influence the effectiveness of the responsive pricing strategy?
- RQ 3: Depending on the disruption length and the height of the price change, how long should responsive pricing be applied?

The definition of RQs has helped us specify continuous factors which are considered to be input variables for the experiment (Sanchez, 2005): (1) duration of disruption, (2) height of the price incentive, (3) length of price change in effect. These factors should not be confused with the input variables of the simulation model, which will be discussed in the next section. The length of disruption studied in this paper varies from 0 to 20 days and could be defined prior to creating a simulation model. The height of the price change (0 to $170) as well as the period of having the pricing strategy active (from the day the disruption starts until ten days after the disruption has been coped with) could only be determined after having a valid and verified conceptual and computerized model with defined outputs. Output variables, called responses, are set to be the overall disruption costs for the supply chain, the proportion of disruption costs reduced by the strategy, and the order fulfilment rate (OFR).

The conceptual simulation model and the computerized simulation model have been developed with the software AnyLogic 7.3.6 in iterative steps and have been combined with validation methods described in Sargent (2013), namely animation, comparison to other models, extreme condition test, and a test for internal validity. Through animation, the model's operational behavior could be displayed and checked as the model moves through time. Our conceptual model extends the comprehensible model designed by Wilson (2007), which examines the effects of transportation disruptions on a five-echelon supply chain with fixed transit times on the inventory levels, by incorporating two products, cost parameters, and price-sensitive demand. Parts of their conceptual model could be inherited and inspected for correctness so that the validity of our conceptual model could be strengthened. The plausibility of our model's responses being caused by extreme levels of input variables, in our case disruptions of 20 days at different parts in the supply chain, demand change to 0 and to 30 units per period, and extreme target inventory levels, has been checked via extreme condition tests. As our demand is modeled stochastically, internal validity is needed to test the variability of our responses. 15 runs with different random seeds lead to a variation coefficient of 0.369% so that our model is considered to be near-deterministic.

According to Montgomery (2012), the subsequent step of conducting a simulation experiment is to define the design of the experiment, which depends on the aim of the experiment, the number of factors, and levels of factors present. Especially for a large number of factors, screening methods are suitable for detecting significant factors via lack of fit tests (Ji and Kang, 2017). Optimization is generally achieved by developing a response surface, which displays the approximate relationships between factors and responses (Sanchez, 2005). Since a complete calculation of all possible factor combinations in the computerized model would take too many runs, different designs, such as full and fractional factorial design, finer grids, space-filling designs, etc., are used to explore the response surface systematically with reasonable effort (Cavazzuti, 2013; Sanchez, 2005). In case of fractional design, linear regressions are used to estimate the relationship between factors and response, whereas the response surface methodology is able to analyze square effects. The smaller the surface area is, the more it is reasonable to approximate the response surface through linear or quadratic models. Uniform design, which is a space-filling design where the examined factor-response signals are spread evenly within the factorial range, is recommended for analyzing non-linear and near-deterministic or deterministic models on a broader surface area with a large number of factor levels (Ji and Kang, 2017; Kleijnen, 2005).

Because our model displays near-deterministic behavior with potentially non-linear effects, we have chosen a uniform design with one run per factor-level. As recommended by Montgomery (2012), instead of running one large experiment, three smaller experiments, each of which is addressed to one of our RQs, are conducted sequentially. The first RQ contains the first factor with 200 levels (0-20 days; steps of 0.1 days, resulting in 2000 runs). The second RQ takes the second factor into account as an additional factor. The first factor is split into 21 levels (0-20 days; steps of one day) and the second factor into 35 levels ($0-170; in steps of five; total of 735 runs). The third RQ is answered by splitting the first factor into three levels (5, 10, and 15 days), keeping the 35 levels of the second level, and adding 15, 20, and 25 levels for the third factor (time period from the start of the disruption until ten days after the disruption has been coped with; total of 2100 runs). A subsequent sensitivity analysis examines the robustness of the previously found extrema concerning the deviation of the structural parameters, namely transit times, level of stock in the system, and variation of the mean customer demand.

4. Model description

4.1. Model assumptions

Before we begin with the description of our model, we must present our core assumptions regarding the organization of our modeled supply chain, the type and character of the disruption(s), and the specification of the modeled mitigation strategy. The assumptions regarding the organization and the information flow in the supply chain have been adopted from Wilson (2007).

Our five-echelon serial supply chain manufactures two products, which are highly but not completely substitutable. The demand of these two products is modeled initially with an equal Gaussian distribution. The mean of the two distributions changes when the responsive pricing strategy is in effect. The supply chain is organized "classically", with each partner receiving the direct demand of its predecessor and smoothing the demand for the subsequent supplier. Lead times are fixed, deterministic, and vary for each link in the supply chain. The model is a continuous model with stocks, orders, demand, and shipments being calculated in each incremental time period. A balance of inventory levels and shipments is achieved by demand smoothing and stock-level feedback.

To measure the effectiveness of our mitigation strategy, a disruption compromises the production of one product, while the second product is not affected directly. In our model, one disruption occurs at the warehouse of a specific supply chain member starting from day 100, destroying its complete inventory instantly, and preventing any shipments for a time span in which the disruption has not been coped with. An exemplary situation could be a fire destroying the goods and critical infrastructure, such as the warehouse management system, shelves, means of internal transportation etc. The length of the disruption is considered to be the time until compensatory infrastructure is established. The impaired supply chain member can still receive goods without being able to process, pack, and ship them. The OFR, which is one of our response and performance measures, is calculated as the ratio of fulfilled customer orders to all incoming customer orders in the time period of day 100 until day 150. The disruption costs are measured by comparing the monetary situation without a disruption having occurred to the specific disruptive scenario. Therefore, this performance measure is independent from the absolute revenue of the supply chain and considers the overall difference in total inventory costs and lost sales. Not included in this performance measures are the costs of damaged infrastructure and penalty cost for late delivery. When we measure the effectiveness of a responsive pricing strategy, we compare the resulting disruption cost to the case of having no strategy in effect.

Responsive pricing, which is also referred to as demand shifting, is an elastic concept covering different strategies for revenue management (Crew et al., 1995). Peak-load pricing is used, for example, by airlines and hotels to shift demand from peak seasons to off-peak seasons and to obtain higher revenues with fixed capacities (Talluri and van Ryzin, 2005). Advance-commitment discounts improve forecast accuracy, reduce inventory fluctuations, and are applicable to non-seasonal products (Choi and Sethi, 2010; Tang, 2006). Besides shifting demand across time, responsive pricing can relocate demand across markets and products. Shifting demand across markets is used with seasonal products, offering a secondary market the leftover inventory of the primary market. Shifting demand across products can be either achieved through product bundling or product substitution (Maheshwari and Jain, 2015). In our case, we refer to responsive pricing as product substitution. To model this price sensitive product substitution, we need to define a demand function which relates price and demand plausibly. A Marshallian demand function, which describes the buying behavior between a number of products to maximize customer utility in microeconomics, models the demand shift to the second product if prices are changed (Nicholson and Snyder, 2012). A linear demand function is used to model the relationship between the price and demand of the first product. This combination ensures that the original price and demand maximizes the revenue of the supply chain's first product. To simplify the model and lessen the computational effort, a price hike of one product leads to a price reduction of the same magnitude of the other product.

4.2. Model structure

SD is a modeling approach which aims to analyze complex and dynamic systems through (partly delayed) cause-and-effect relationships and information feedback. According to SD, the dynamic aspects of a system stem from its inherent, endogeneous structure (Sterman, 2000). In SD, stocks (also called levels) form entities that accumulate or deplete over time. The rate of change in a stock is referred to as a flow (or rate). Stock-flow diagrams visualize the general relationship between stocks and flows of the system, whereas causal loop diagrams describe the general interactions of the system's general components and, therefore, capture the basic structural behavior of a system (Ford, 1999). Variables of causal loop diagrams connected by arrows and expressing positive or negative relationships can form causal loops, which can either balance or reinforce fluctuations of stocks (Kirkwood, 1998; Sokolowski and Banks, 2009). A set of equations, which in the case of a continuous model are stated as integral equations over time, describe the cause-and-effect relationship in a detailed manner. In the course of simulation, the state of the system is updated incrementally over time (Duggan, 2016).

This section outlines the general structure of our conceptual model, which is based on the model of Wilson (2007), and describes the structure of the modeled supply chain, the general and abstract behavior of the model in the form of a causal-loop diagram, and a set of general equations.

The material and information flow of the modeled five-echelon supply chain between each partner and the generic customer is depicted in Figure 1. The raw material supplier, wholesaler, and retailer are not producing and are considered as having one warehouse each. Both the supplier of subassemblies and the manufacturer carry out production steps with individual

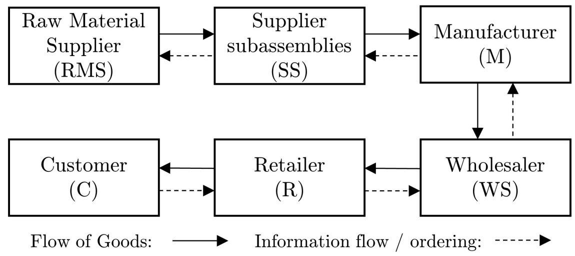


Figure 1: Structure of the modeled supply chain

production lead times and, therefore, operate an inbound and an outbound warehouse each. Demand information is only available in the form of incoming orders from the direct upstream partner. The incoming orders are smoothed, adjusted depending on the individual inventory levels, and transferred as outgoing orders to the upstream partner. The terms and conditions of sale and delivery are defined as ex works: goods in transit belong to the downstream partner. Since the complete causal-loop diagram visualizing all individual supply chain members would be too extensive to illustrate here, Figure 2 displays a generic causal-loop diagram of our model, which can be individualized. Figure 2 details the cause-effect relationships of a focal supply chain member and portrays the transition to the immediate downstream and upstream partner. The variables and loops repeat themselves if further members are included between the dashed, serpentine lines. If a supply chain partner does not produce, the variables in the grey area will become obsolete so that the

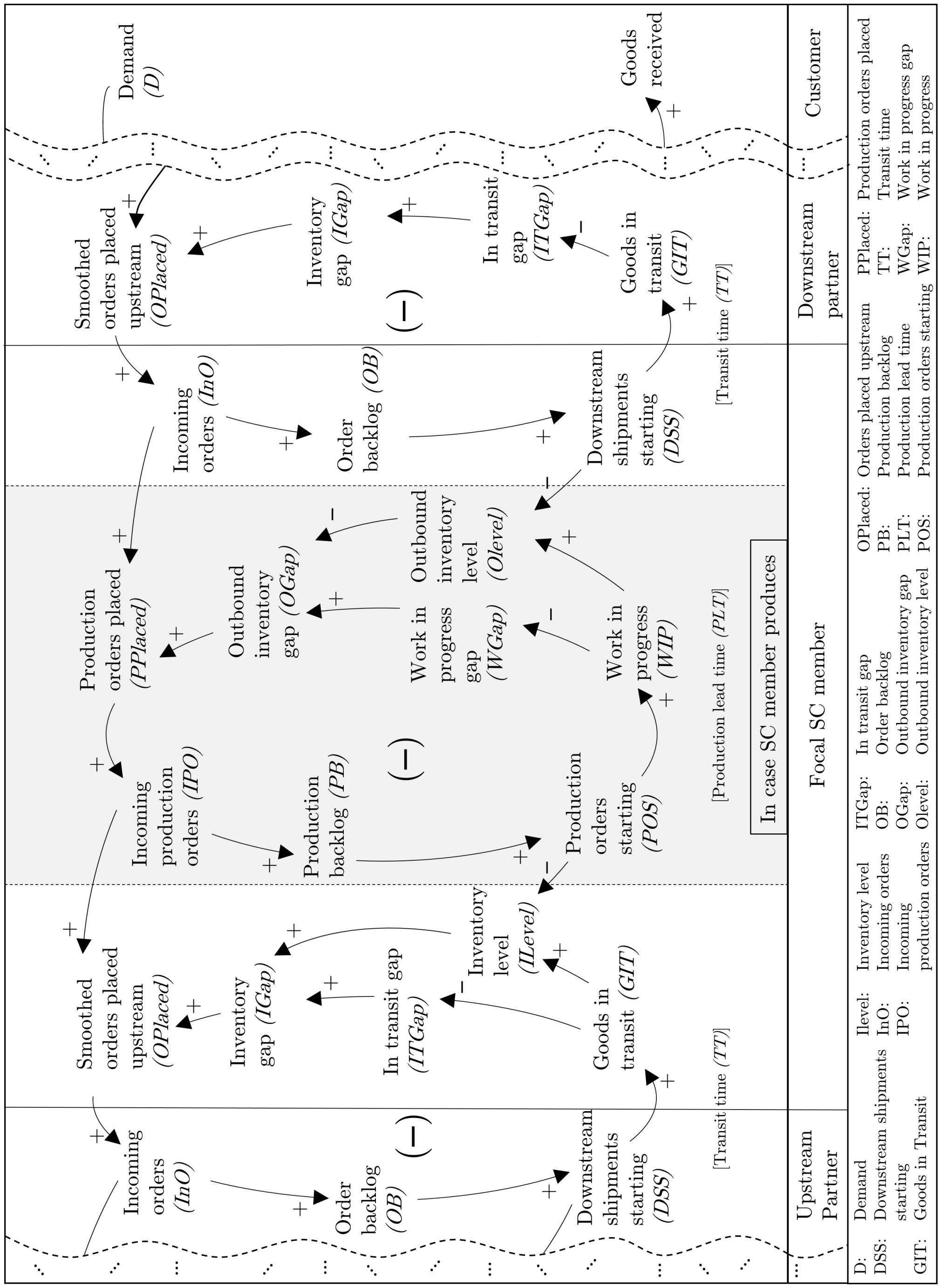


Figure 2: Causal-loop diagram of the modeled supply chain

variables "Incoming orders" and "Goods sent downstream" can be linked to "Smoothed orders placed upstream" and "Inventory level". While the "+" sign attached to arrows indicates a positive influence on the subsequent variable, the "−" sign displays a reverse and negative influence. The three loops discernible in Figure 2 are self-balancing, which is caused by inventory feedback that helps the system eventually become balanced if no exogenous perturbations occur.[2] For example: an increase in production orders placed will raise the incoming production orders, the production backlog, the production orders starting (depending on the preceding inventory level), and the work in progress. This reduces the work in progress gap as well as the outbound inventory gap, which lowers and therefore balances the production orders placed. The retailer is the only member which receives direct demand information. For all other partners, smoothed and adjusted orders are placed upstream. The variable "Smoothed orders placed upstream" is equivalent to the variable "incoming orders". Incoming orders are received and the orders placed upstream are calculated by the corresponding supply chain member. Orders placed by the downstream partner are calculated by adjusting the smoothed demand ($\bar{D}(t)$) with respect to the inventory gap of the ordering member (abbreviations of the variables can be found in Figure 2, equations adopted from Wilson (2007), structural equations for production are visualized in parentheses, the current simulation time is described with t):

$$OPlaced(t) = \max\left\{\frac{IGap(t)}{TT} + \bar{D}(t); 0\right\}$$

$$\left(PPlaced(t) = \max\left\{\frac{OGap(t)}{PLT} + \bar{D}(t); 0\right\}\right)$$

In case of a production, incoming orders are not smoothed again but adjusted by the outbound inventory gap. The demand is smoothed ($\bar{D}(t)$) by using

[2] In SD, self-balancing loops emerge if the amount of negative relationships is odd in total, whereas positive, reinforcing loops are formed by an even number of negative relationships in total (Bala et al., 2017).

a moving average with a smoothing period of a. The retailer smooths the actual demand $D(t)$:

$$\bar{D}(t) = \frac{\int_{k=t-a}^{t} D(k)dk}{a}$$

The other partners smooth their incoming orders as follows:

$$\bar{D}(t) = \frac{\int_{k=t-a}^{t} InO(k)dk}{a}$$

The inventory gap depends on the constant target level of inventory ($ITarLevel$), the inventory level itself, and the pipeline gap of the in transit inventory:

$$IGap(t) = ITarLevel - ILevel(t) + ITGap(t)$$

$$(OGap(t) = ITarLevel - OLevel(t) + WGap(t))$$

By analogy, the in transit inventory gap (work in progress gap) is calculated by comparing the in transit inventory (work in progress) with the in transit target inventory ($TarLevelIT$) (work in progress target inventory ($WIPTarLevel$)):

$$ITGap(t) = TarLevelIT - GIT(t) \qquad (WGap(t) = WIPTarLevel - WIP(t))$$

The goods in transit can be calculated by accumulating the goods sent downstream for the transit time period:

$$GIT(t) = \int_{k=(t-TT)}^{t} DSS(k)dk \qquad \left(WIP(t) = \int_{k=(t-PLT)}^{t} POS(k)dk \right)$$

The quantity of shipments which is sent downstream (production orders starting) depends on the height of order backlog (production backlog) and the corresponding inventory levels:

$$DSS(t) = \min\{OB(t); ILevel(t)\} \qquad (POS(t) = \min\{PB(t); OLevel(t)\})$$

Incoming orders (production orders) increase the order backlog (production backlog), which is decreased by the amount of goods sent to the downstream partner (amount of started production orders):

$$OB(t) = OB(t - dt) + InO(dt) - DSS(dt)$$

$$(PB(t) = PB(t - dt) + IPO(dt) - POS(dt))$$

The inventory level fluctuates because the partner is receiving upstream goods and shipping goods downstream as well. Shipments arrive with a time delay of the transit time (production lead time) referring to the moment the order is sent downstream (the production started):

$$ILevel(t) = ILevel(t - dt) + (DSS(t - TT) - DSS)dt$$

$$(OLevel(t) = OLevel(t - dt) + (POS(t - PLT) - DSS)dt)$$

After having described the general behavior of our SD model, model parameters need to be defined to specify our supply chain characteristics.

4.3. Model parameters

If a system exists in reality, parameters need to be carefully selected and validated. Since we could not obtain real supply chain data and our aim is to study the variation of effectiveness regarding the parameter variations of our simulation experiment, we decided, also for validity reasons, to adopt the majority of the parameters from Wilson (2007). Therefore, the demand of both products is set initially at 10 pieces per day with a standard deviation of two pieces per day. The smoothing parameter has been set at twice the lead time, as recommended by Disney and Towill (2002), to reduce the bullwhip effect. Holding costs as well as product prices need to be defined because the model of Wilson (2007) does not incorporate monetary values. Our model's parameters can be found in Table 1. As mentioned in subsection 4.1 and due

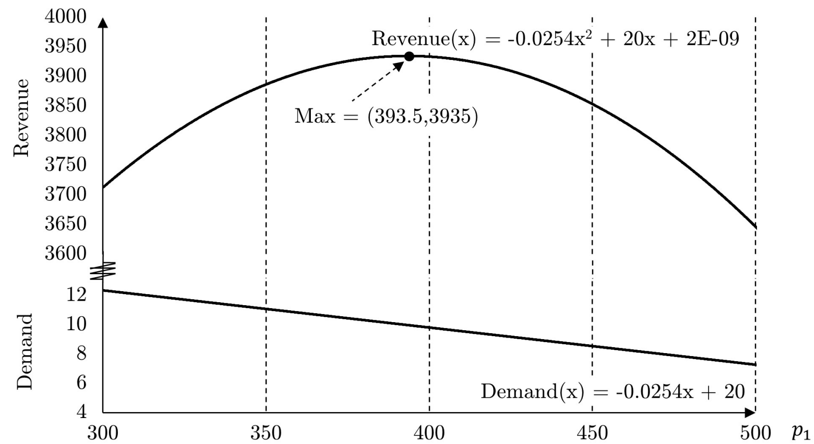


Figure 3: Demand function of first product

to complexity reasons, both products start with the same price and demand, and a Marshallian demand function combined with a linear demand function changes these parameters when the pricing strategy is active. The holding costs per day and product, expressed as a whole number, are set at around 2-3% of the goods' value. The prices of the products are calculated and set to a value which guarantees that each member of the supply chain earn a profit of $100 each day in a balanced state of the system.

The demand and revenue function with respect to the price of the first product p_1 can be seen in Figure 3. The functions have been defined to maximize the revenue of the first product at our initial demand and sales

		RMS		SS				M				WS		R	
	Raw Material	Raw Material Concentration	Stock Raw Material	Transit	Stock Raw Material	Prodution	Stock Subassemblies	Transit	Stock Subassemblies	Production	Stock Finished Goods	Transit	Warehouse	Transit	Point of Sale
Initial Inventory [pcs]	∞	60	120	60	90	50	100	40	60	40	80	20	30	10	15
Target Inventory [pcs]	-		120		90		100		60		80		30		15
TT / PLT [ds]	-	6	-	6	-	5	-	4	-	4	-	2	-	1	-
Smoothing Par. a [ds]	-	12		10				8				4		2	
Sales Price [$/pc]	10	56		163.5				313.5				363.5		393.5	
Holding costs [$/pcs·ds]	0		2		2		5		5		8		8		8
pcs = pieces; ds = days															

Table 1: Model parameters

price. A Marshallian demand function for two products (prices p_1, p_2) is used to maximize the consumer's utility U subject to the available income y and choices of consumption quantity x_1 and x_2 (Coto-Millán, 2012):

$$\max \;\; U(x_1, x_2) \qquad \text{subject to} \;\; y = p_1 x_1 + p_2 x_2$$

In our case, y is set to two times the maximum revenue of one product: $y =$ $\$7,870$.

If the demand of the two products is not totally substitutable, the absolute revenue can be adjusted by a function which reduces the revenue conditionally according to the height of the price change. Depending on the price change, the new price of product 1 leads to a new demand quantity based on the already presented demand function. The demand of the second product can be calculated with the Marshallian demand function because the new price p_2 is also known.

5. Discussion of simulation results

When conducting simulation experiments and collecting output data, one important aspect is the proper handling of the so-called initial transit or warm-up period. In most cases, the system needs a certain length of time to be filled with entities to reach a steady state. If this warm-up period is not considered adequately, the simulation responses can be biased and misinterpreted unknowingly. Two main strategies are used: data deletion, which strives to delete the data of the warm-up period, and intelligent initialization, which aims to create a realistic initial condition at the start of the run (Robinson, 2007). In our case, the disruption(s), and therefore the collection of data, should occur after the system has reached its balance. A variety of methods exist to help estimate the initial transient (Currie and Cheng, 2016): graphical, heuristic, statistical, hybrid methods, and initial bias tests.[3] We use the graphical Welch's Method (Welch, 1987), which bases on the calculation and plotting of moving averages and subsequent visual in-

[3]For a comprehensive summary of initial transit estimation methods, we refer to Robinson and Ioannou, 2007.

spection, and the heuristic method of marginal standard error rule MSER-5 (White, 1997), which minimizes the width of the confidence interval of the remaining simulation output data if different lengths of initial transient data are deleted. Especially the MSER-5 heuristic is considered to be very accurate (Mahajan and Ingall, 2004; Pasupathy and Schmeiser, 2010; Franklin and White, 2008; White and Spratt, 2000). To measure the system's balance, we consider the current inventory costs of each supply chain partner and each product as the output parameter for the tests. Welch's method and the MSER-5 heuristic resulted in a warm-up period of 90 days so that the disruption(s) are set to take place on day 100. The termination point of each run has been determined analogously. On day 250, the system's equilibrium state is reached in case a disruption with a maximum length of 20 days occurs.

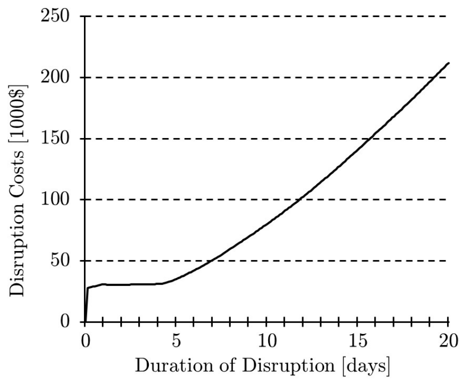
In this section, the RQs will be tackled chronologically. The Kriging component of the software *STATGRAPHICS Centurion XVII* has been used to create response surfaces that have helped answer RQ 2 and 3. Kriging is an interpolation algorithm which has been developed in geostatistics to estimate spatial features, such as porosity levels (Nazarpour et al., 2014) and groundwater quality (Al-Mashagbah et al., 2011). It is also used in deterministic and near-deterministic simulation models to estimate global behavior for larger experimental areas (Kleijnen, 2009). In all interpolation algorithms, the value of a parameter is estimated as a weighted sum of data values of the surrounding locations. With Kriging, weights are optimized using a fitted variogram function, which contains the variablility between pairs of points at various distances (Oliver and Webster, 2014).[4] In our

[4] A comprehensive and detailed look at Kriging can be found in Kleijnen, 2009, Oliver and Webster, 2014, and Van Beers, 2005.

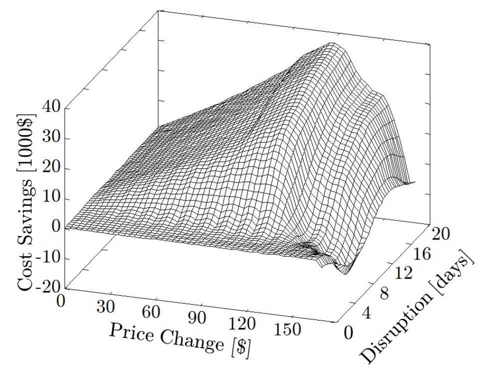
case, an exponential function fits the variogram data best with a coefficient of determination (R^2) of 76.21% (Figure 4b), 91.37% (Figure 4c), 71.13% (Figure 4d), 92.00% (Figure 4e), and 95.60% (Figure 4f).

Our first RQ analyzes the influence of the disruption length on the overall cost of disruption. While researchers consider supply chain disruptions as dramatic and costly chains of events (Cedillo-Campos et al., 2014, Sheffi and Rice, 2005), there is a lack of research analyzing this aspect in detail. To our knowledge, the only study regarding this topic is the empirical work of Hendricks and Singhal (2005), which examines the effect of disruptions on the stock value of a company. Severe stock price reduction and a negative long-term effect could be detected by the authors. The results of our first simulation experiment, which varied the disruption length incrementally from 0 to 20 days, can be seen in Figure 4a. The direct monetary consequences of a disruption, described in section 4.1, amount to $27,934. This figure consists of the value of the items destroyed immediately and the subsequent inventory fluctuations aiming to refill the inventory gaps. The OFR remains at 100.0% until a disruption length of 4.4 days is reached. The overall costs merely increase up to this length, and the inventory levels of the warehouse and retailer can withstand the disrupted period. A non-linear behavior can be seen if the supply chain encounters a disruption time span of more than five days. If the disruption lasts for eight days, the overall cost rises to $60,272 with an OFR of 92.3%. A 10-day disruption leads to overall disruption costs of over $80,000, and the OFR drops to 87.5%. A 15-day disruption causes more than $140,000 (OFR of 73.3%) in damages, while a 20-day disruption causes $211,928 in damages and an OFR of 55.0%. Our model shows that non-linear effects emerge if stock-out events occur. The system starts to overreact and experiences heavy inventory fluctuations which need time to rebalance.

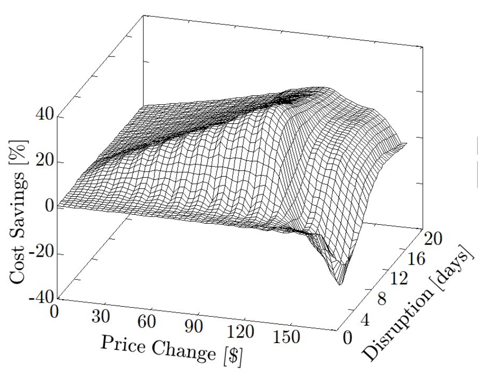
Figures 4b and 4c help us answer the second RQ. This RQ studies the effect of the responsive pricing strategy and the influence of the height of price change on the overall disruption costs. The pricing strategy is assumed to be in effect for the exact disruption length. The ordinate of Figure 4b expresses the absolute cost savings in case a pricing strategy is used. A responsive pricing strategy does not bring any positive results for short-term disruptions up to four days. If a price change of more than \$170 is configured, the consequences for short-term disruption can even be detrimental. Price changes up to \$135 are useful for a disruptive period of over four days and especially beneficial for marginal cost savings in the time period when the first stock-outs occur (disruptions longer than 4.4 days). A price change of \$150, for example, is useful for disruptions longer than eleven days. For a disruption length of five days, a price change of \$60 is optimal and leads to \$4,285 (OFR +1.3% to 100%) saved. In case of a 10-day disruption, \$25.933 can be saved with a price change of \$125, and the OFR can be increased by 6.9% to 94.4%. This optimum drops for an 11-day disruption to \$120 and stays advantageous also for a 15-day (\$31,817 saved; OFR +7.4% to 80.7%) and a 20-day disruption (\$36.791 saved; OFR +8.0% to 63.0%). High price changes are risky because the usefulness decreases rapidly. Figure 4c displays the relative cost savings with respect to the disruption costs of the corresponding length of disruption. This figure shows that responsive pricing can be especially useful for disruption lengths of four to ten days. In our case, a maximum of 33.7% (\$20,301; +5.3% to 97.6%) can be achieved by a price change of \$120 and a disruption length of eight days. Although, for example, the absolute cost savings in Figure 4b steadily increase with a price change of \$120, the percentage of costs saved decreases with the same price change



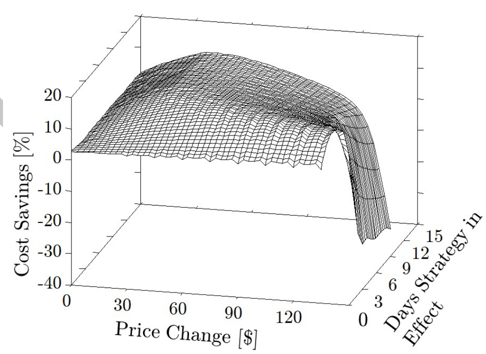
(a) Disruption costs with no strategy in place



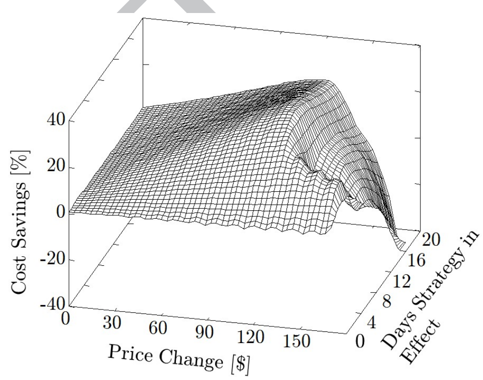
(b) Absolute Cost savings when pricing strategy in effect



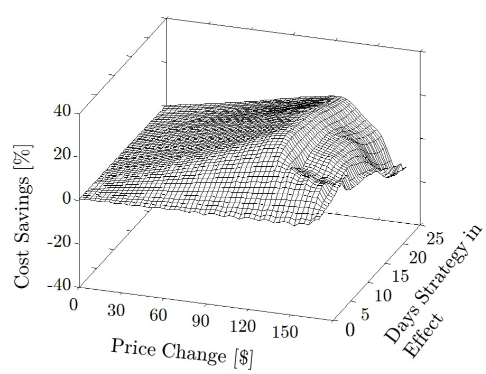
(c) Proportion of Disruption costs saved by pricing strategy



(d) 5-Day Disruption: time span variation strategy is active



(e) 10-Day Disruption: time span variation strategy is active



(f) 15-Day Disruption: time span variation strategy is active

Figure 4: Results of simulation experiments

after eight days. The non-linear growth of the disruption costs outweighs the absolute, and also growing, cost savings with the pricing strategy. The inspection of the second RQ can be summarized as follows: In our model, a responsive pricing strategy can have a positive effect, depending on at least the length of the disruption and the height of the price change. For short disruptions, it is helpful to not change prices as much as in case of longer disruptions. Very high price changes are risky because they are detrimental for short-term disruptions. From a specific disruption length onwards, an optimal price change range can be determined (here $120-125).

After having answered the second RQ, the third RQ leads us to the question of what influence the responsive pricing's time length has on the strategy's overall effectiveness. The previous RQ set the time span of the active responsive pricing strategy to the exact disruption time. In reality, there is no exact point in time when it can be said that a company has overcome a disruption and is fully functional. Sheffi and Rice (2005) distinguish between disruption phases, such as initial impact, preparation for recovery, and a recovery phase in which the performance of the company slowly but steadily increases. Still, the answer to this RQ gives hints on how this reactive strategy could be applied. Three disruption lengths (5, 10, and 15 days) have been analyzed by varying the duration of the pricing strategy from zero days (time when disruption started) up until ten days after the modeled disruption has ended. Figure 4d shows the response surface in the case a disruption of five days has occurred. In order to see the detailed contours in the advantageous area, the chart displays price changes up to $135. Higher price changes lead to strong disadvantages. From answering the previous RQ, it is obvious that the pricing strategy for a short disruption period is helpful but not as effective as it is against longer disruptions.

The usefulness increases from changes of $0 to $55. A steep decline in the effectiveness of the strategy can be seen with price changes higher than $120. The relative cost savings first increase each day until they reach a climax and steadily drop with each active day. The stronger the chosen price change, the earlier the climax of usefulness. In case a price change of $60 is intended, an optimal length of five days (same as disruption length) leads to 12.19% ($4,285; OFR 100.0%) cost savings. A price change of $100 already reaches its climax of 11.4% after three days. The previously found optimum at a disruption length of five days (price change $60) can be further improved by a slightly reduced price change ($55) with a longer time in action (6 days): 12.21% ($4,292; OFR of 100%). Figure 4e displays the surface level in the case of a 10-day disruption. Analogous to Figure 4d, the usefulness first increases with higher prices until an optimum is reached. Then the advantages of the strategy quickly disappear for price changes higher than the optimum, and the pricing strategy causes negative effects. The optimal operating time of each price change elongates until the optimal price change is reached. A $35 change in prices leads to a maximum of 9.39% of costs saved ($7,588 OFR of 88.9%) if it is in effect for seven days. A $60 price change needs eight days to reach its optimal potential of 15.90% ($12,848 saved; OFR of 90.1%). A $100 change can already save more than a quarter of all costs (26.88%; $21,721; OFR of 92.5%) if installed for nine days. In our case, the overall optimal pricing strategy for a 10-day disruption is a price change of $125 for nine days, which can save up to 32.18% ($25,998, OFR of 93.9%) of the disruption costs. The price change should optimally be finished one day before the 10-day disruption has been coped with. If it is in effect for the complete disruption time, the strategy is still nearly as good as the optimum: 32.09% ($25,932; OFR +0.5% to 94.4%). Figure

4e shows the response surface when a 15-day disruption has occurred. As the disruption cost grows disproportionately to the disruption length, the maximum cost savings of the optimal pricing strategy are lower than in the case of a 10-day disruption. The overall behavior of the chart is similar to Figure 4d. If the disruption is in effect for a longer period, a price which is slightly higher than the optimal is not as damaging as it is for a shorter disruption length. The optimal strategy for this risk situation would be a price change of \$125 for nine days that leads to a cost reduction of 25.03% (\$35,356; OFR of 81.1%). This strategy would be better than the previously calculated optimum of a \$120 price change leading to a reduction of 22.53% (\$31,817; OFR of 80.6%). Our third RQ can be answered as follows: The time span that responsive pricing is in effect does have an impact on the overall cost savings. Our results show that the previously found optimal price changes can be further improved by considering slightly different prices and operating times of the strategy. Nevertheless, having the pricing strategy in effect for the exact disruption time leads to near-optimal results. This indicates that companies do not have to anticipate the cessation of a disruption to switch strategies in advance but can stop the reactive strategy when the disruption has been coped with for the most part. Finding the right price when facing a disruption is more important than the strategy's operating time. Our results do not indicate that the pricing strategy should be in place for a significantly longer time than the direct disruption time.

6. Sensitivity analysis of structural parameters

After examining the influence of the price change and the length of time the pricing strategy is in effect, we now want to shift the attention to the effect of structural parameters on the model's output. A sensitivity analysis aims to compute the effect of changes in input values or assumptions on the model's output (Saltelli and Scott, 1997). The design of the sensitivity analysis depends on the model's purpose (Borgonovo, 2017). Borgonovo and Plischke (2016) distinguish between five different sensitivity analysis settings, namely factor priorization, factor fixing, model structure, direction of change, and stability setting. While factor priorization aims to identifiy the key drivers of a model, factor fixing looks to identify the least influential variables in order to confidently fix them at a specific level with the aim of reducing computation time. The model structure setting calculates if interrelationships between input factors play a relevant role. The direction of change setting determines if an increase in an input variable increases or decreases the output locally or globally, while the stability setting seeks to find out if changes in the input variables lead to a change of the preferred alternative. The five settings can be either applied locally by changing one variable at a time around a predetermined area of interest or globally by assessing the changes in one or more variables on the total response surface (Cacuci, 2003). As our model aims to support the decision process of supply chain risk managers, we want to determine how much the structural input parameters may vary before the optimal pricing strategy changes, which also helps us to prioritize the input parameters accordingly. Considering the complexity and number of parameters of our model, a global analysis is not manageable. We therefore apply the local stability setting. We focus on the disruption lengths of 5, 10, 15, and 20 days and examine the previously found optima. To keep the viewpoint of the practitioner, we assume that the strategy is active for the complete disruption time. This design is interesting for the supply chain's decision makers as it may help to determine which input parameters have the most effect on the decision. Depending on how

Disruption Time [days]	Stock Level			Mean Demand			Transit Times		
	lower bound [%]	range [%]	upper bound [%]	lower bound [%]	range [%]	upper bound [%]	lower bound [%]	range [%]	upper bound [%]
5	-0.07	2.82	2.75	-1.75	2.41	0.66	-45.05	68.06	23.01
10	-0.71	6.68	5.97	-23.60	27.72	4.12	-2.62	7.39	4.77
15	-5.32	5.72	0.40	-2.11	28.08	25.97	-2.62	7.94	5.32
20	-1.30	5.51	4.21	-13.52	18.38	4.86	-4.00	6.10	2.10

Table 2: Sensitivity analysis regarding the height of the customer demand, stock value, and transit times

critical the input parameters turn out to be, the decision makers need to assess if the data basis of the input parameters is accurate enough or if more effort has to be put into improving their accuracy. The most important structural parameters which influence our model's output are the level of stock in the system, the transit times of transportation processes, and the level of customer demand. The level of stock and the transit times are adjusted by the same percentage for all supply chain entitities to ensure a manageable computational burden and also to reflect that we assume that the same effort for data retrieval has been put in by all entities. Table 2 illustrates the necessary relative lower and upper deviation of the three tested parameters as well as the relative range in which the solution does not change. It can be seen that optimal responsive pricing strategies are quite robust, but the deviation is dependent on the length of the disruption. The level of stock is, overall, the most sensitive parameter with a relatively stable range of deviation from 2.82 to 6.68%. To ensure the validity of the model, decision makers need to especially consider the accuracy of sensitive input parameters. The results regarding the mean demand and the transit time draw a more differentiated picture. While the optimal strategy is rather insensitive to changes in transit times in case of a five-day disruption, the optimum regarding a disruption of the same length is particularly sensitive to changes in the mean demand. A five-day disruption causes the first out-of-stock situations in the system, suggesting that the mean demand has a critical influence. This relationship reverses when the disruption time is 10, 15, or 20 days, meaning that accurate estimations of the transit times are more important.

7. Conclusion, limitations, and future research

This paper has concentrated on quantifying the destructive monetary effects of disruptions and evaluating the reactive strategy of responsive pricing in the face of different lengths of disruptions. For this purpose, the SD model of Wilson (2007) has been extended to a two-product model with monetary parameters. A simulation study, which has been divided into three simulation experiments, has been conducted to answer the formulated RQs. Since a full-fractional Design of Experiments was not manageable, a uniform space-filling design has been selected for the data basis of the response surface. The surfaces themselves have been interpolated with a Kriging approach.

Our results quantify the fact that the length of the disruption has a disproportionate influence on the disruption costs the supply chain is faced with. While researchers stress proactive measures, our study has shown that the reactive strategy of responsive pricing can lead to significant cost savings for the supply chain. In our model, over one third of the disruption's damage on the supply chain could be averted. Especially good results could be achieved when a medium-term disruption of around six to twelve days has occurred.

The influence of the height of the price change has shown to be of more importance than the operating time of the strategy. From medium-term disruptions onwards, a price range area could be determined which leads to near-optimal results if the strategy is active for the disruption length. Even though the results could be improved by considering different durations of the strategy, the results are good enough to recommend a use of this strategy for the acute time of disruption. It is not recommended to use higher price changes than the optimum price change, because it could be shown that the effectiveness of this strategy deteriorates significantly. It is also detrimental to let the strategy be active for a significantly longer period than the disruption length. The optimal strategies with reference to the disruption lengths are relatively robust when facing changes of structural parameters. The level of stock is the most critical input parameter and needs to be assessed precisely, while the required accuracy of the considered transit times and the mean demand is dependent on the length of the disruption faced.

To our knowledge, responsive pricing has not been thoroughly investigated in the context of supply chain disruption yet. Pricing in general has been long studied in the field of revenue management, which aims to maximize revenue for a fixed capacity of a product or service by saving the capacity for the most valuable customer by proper capacity allocation (Cheragi et al., 2010). It is particularly interesting for industries with fixed capacity and a highly uncertain demand such as the airline, the hotel, and car rental industry etc. Its planning problems can be divided into demand forecasting, inventory control, and dynamic pricing. The still rather small research area of joint pricing-inventory models analyses pricing-inventory decisions in the context of multiple substitutable products (Aydin and Porteus, 2008; Hsieh and Wu, 2009; Karakul and Chan, 2010; Wilson and Anderson, 2015).

Dynamic models are used to study pricing with fixed capacity in case of a single-product (Feng and Xiao, 2006; Akan et al., 2013). Considerations of multiple products and dynamic price choices are still rare (Akçay et al., 2010; Dong et al., 2009). Our work extends the research of revenue management by considering pricing under the influence of disruptive shocks in capacity and extends the research of supply chain risk management by applying strategic pricing decisions as a reactive strategy to face supply chain disruptions.

There are several limitations to our work. First, consumers can often choose between a variety of competing products, which arguably decreases the effectiveness of responsive pricing. Second, a complete product substitution is not realistic because a portion of the customers will rethink their purchasing desire. Third, customer behavior is a complex topic of research and different demand functions could have been incorporated. Finally, real supply chain data could not be acquired for this study. Although we could model basic interactions of this strategy, the usefulness of responsive pricing is dependent on the individual supply chain scenario. Therefore, with this study we like to motivate practitioners to offer real supply chain data to improve prospective models.

The growing research area of SCRM offers a variety of research potentials. It can be argued that the body of SCRM literature shows a discontinuity between conceptual and quantitative research. While conceptual research concentrates on types of risk definitions, classifications, frameworks, and general mitigation recommendations, quantitative approaches focus mainly on specific supply chain planning problems under the influence of disruption risks. Network level simulation models are promising because they have the potential to build a bridge between these research areas. With our work, we want to motivate researchers to develop more holistic, dynamic, and interdependent risk modeling approaches and to assess more risk mitigation strategies as well as combinations of them quantitatively. Empirical studies on the repercussions of supply chain disruptions and effectiveness of strategies are also an important topic of interest.

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- A System Dynamics approach to study responsive pricing in a disrupted supply chain
- Simulation-based cost analysis subject to the disruption period and pricing policy
- Significant reduction of disruption costs in our exemplary five-tier supply chain
- Optimal height of price change depending on the duration of the disruption
- Operating time of the strategy determined by the height of the price change