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SIMULATING AND EVALUATING SUPPLY CHAIN DISRUPTIONS ALONG AN END-TO-END SEMICONDUCTOR AUTOMOTIVE SUPPLY CHAIN

Friedrich-Maximilian Jaenichen
Christina Johanna Liepold

Abdelgafar Ismail
Christian James Martens
Volker Dörrsam
Hans Ehm

Technical University of Munich
Arcisstraße 21
80333 Munich, GERMANY

Infineon Technologies AG
Am Campeon 1-12
85579 Neubiberg, GERMANY

ABSTRACT

The COVID-19 pandemic is an unprecedented public health and economic crisis. It dramatically impacted different industries, and presented an unforeseen challenge to the automotive industry and its supply chain (SC). We model a system dynamics simulation to demonstrate the behavior of a multi-echelon SC responding to different end market scenarios. The model results highlight challenges that arise for a semiconductor automotive SC not only during, but also after a disruption like the COVID-19 pandemic: strong demand dynamics which cause substantial operational consequences. The model evaluates how upstream companies in the automotive SC suffer from the disruption in terms of amplitude and duration. In order to mitigate these challenges, a close collaboration among players in the SC can increase robustness of the overall SC during unforeseen events like the pandemic.

1 INTRODUCTION

COVID-19 is an infectious disease caused by the newly discovered coronavirus named SARS-CoV-2 (Lai et al. 2020). The COVID-19 crisis affected everyday life and accelerated changes across different domains and businesses. The COVID-19 outbreak represents a special scenario of supply chain (SC) risk that is characterized by three features: highly unpredictable and long-term black swan disruption, simultaneous disruption resulting in ripple effect propagation along SC, and concurrent impacts on demand, supply and logistics (Ivanov 2020).

Logistics and supply disruptions result from multiple lockdowns imposed by governments around the world to eradicate the disease, demand disruptions are driven by sales drops, e.g., in the automotive industry during the lockdowns. In times of crisis companies tend to take strategic decisions to improve their financial position and maintain liquidity. Strategic decisions such as reducing inventory levels or closing manufacturing facilities have substantial operational consequences especially when the demand recovers at a later stage (Udenio et al. 2015). These consequences include large inventory dynamics and loss of sales due to failure to react fast enough to cope with the demand rebound. It is very important, especially for semiconductor companies and other upstream companies in the SC, to keep track of their inventories and the cumulative lead times in order to guarantee the best recovery scenario, which may be independent of the timing and the pattern of the end market demand developments (Fransoo & Udenio 2020).

The semiconductor industry is characterized by short product life cycles due to fast technological development and the doubling in the number of transistors on computer chips according to Moore's law (Moore 1998). Therefore, most semiconductor companies face highly volatile markets causing

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inefficiencies in their current supply-demand planning systems specifically in time of upheavals (Aytac & Wu 2013). This creates an urgent need for an agile, adaptable, and aligned SC to master volatile market situations – a concept known as Triple A SC to achieve a competitive edge (Ehm et al. 2011; Lee 2004). The semiconductor industry is a highly capital intensive industry, and capacity lead times can span up to twelve months reducing the flexibility of reacting to changes in demand (Lee et al., 1992). Finally, the complex and lengthy semiconductor manufacturing process results in production lead times up to six months or longer both in frontend and backend production (Mönch et al. 2011). Due to the long lead times any small changes in the end market demand result in major fluctuations upstream in the SC – a phenomenon known as the bullwhip effect.

The bullwhip effect describes increased order variability as the orders move upstream in the SC (Lee et al. 1997a). It can result in tremendous disturbances to manufacturing firms and is the origin of the boom and bust in production cycles. Operational disturbances, e.g., excessive inventory as in the early months of the COVID-19 crisis, lasted for several months, and resulted in near-zero orders for the upstream companies. This was subsequently followed by inventory stock outs and chip shortages for long-lead time products (Fransoo & Udenio 2020). Lack of information sharing and long-lead times worsen the situation for upstream companies which are calling for more transparency and collaboration along the end-to-end (E2E) SC to reduce the bullwhip effect.

In our simulation study we aim to find a valid explanation for the severe demand and inventory dynamics observed in upstream companies caused by end market drops and possibilities to mitigate bullwhip effects along E2E SCs. On the one hand, this paper provides an evaluation tool for semiconductor manufacturers to understand the dynamics caused by an end market disruption. On the other hand, we determine the effect of behavioral actions on the overall SC performance and therefore provide managerial insights on mitigation strategies.

This paper is organized as follows: Section 2 presents related literature followed by the description of the methodology in Section 3. The results of the simulation model are discussed in Section 4. Finally, the paper ends with concluding remarks and managerial insights in Section 5.

2 LITERATURE REVIEW AND RESEARCH BACKGROUND

This section presents a threefold overview of the related literature on the topic. The first part about SC risk management provides an overview of the term and related research. The second part addresses the bullwhip effect phenomenon and its presence in literature and presents an overview of the occurrence of this phenomenon during the COVID-19 crisis in the automotive industry. The third subsection of the literature review discusses the body of literature related to the simulation of E2E SCs.

2.1 Supply Chain Risk Management

The topic of SC risk management has been extensively researched and studied in recent years not only due to the outbreak of COVID-19, but also because of previous disturbances. SC risks are comprised of multiple facets and can be classified into operational risks such as lead time and demand fluctuations (Ivanov 2020), and disruption risks such as the nuclear disaster in Japan (Park et al. 2013). Disruption risks are considered black swan events, which occur rarely, but have a great impact (Hosseini & Ivanov 2020; Ivanov et al. 2017; Ivanov 2020). All SC risks have a major impact on the SC network design structure as some manufacturing facilities, suppliers and distribution centers, and transportation lanes go offline on short-term notice (Ivanov 2020; Singh et al. 2012). Hendricks & Singhal (2005), Tomlin (2006), Craighead et al. (2007), Blackhurst et al. (2011), and Bode et al. (2011) focus on the SC risks, the basic reasons that cause the disruptions and the impact of these risks on the SC performance and execution in addition to providing frameworks for the analysis and evaluation of SC risks. Studies by Hora & Klassen (2013), Chopra & Sodhi (2014) and Simchi-Levi et al. (2015) point out the importance of recovery policies and the design of resilient SCs to cope with disruption events.

Pandemic outbreaks such as COVID-19 are often characterized by high degrees of uncertainty, a propagation of disruption in the SCs, i.e., the bullwhip and ripple effect, and a long-term existence of the disruption. Compared to other disruption risks, epidemics start on a small scale, scale fast, and spread broadly. Previous examples, amongst others, include SARS, Ebola and the Swine flu (Ivanov 2020). The COVID-19 pandemic shifted SC management from pure efficiency towards resilience. Because of the lean and the globalized nature of SCs, many companies faced particular problems during the COVID-19 outbreak (Ivanov 2020).

2.2 Bullwhip Effect and Operational Consequences

The bullwhip effect is a well-known topic and has received a lot of research attention. Lee et al. (1997b) describe the bullwhip effect as a phenomenon characterized by two aspects: demand distortion and variance amplification. Demand distortion describes that orders tend to have larger variance than sales while variance amplification describes the amplification of this distortion as it propagates upstream. The bullwhip effect is a widely studied cause of demand information distortion in SCs (Chen et al. 2017). Ivanov et al. (2014) and Ivanov (2017) distinguish the bullwhip effect and the ripple effect which may originate from disruptive risks stemming from structural disruptions in the SC.

Furthermore, Lee et al. (1997a) define four major causes of the bullwhip effect: demand forecast updating, order batching, price fluctuation, and rationing and shortage gaming. They conclude that the combination of these four causes and the decision-making process of managers together determine the bullwhip effect. The bullwhip effect and the origins of oscillations and business cycles are a focus of extensive research which dates back to the early work of Forrester (1958) on a systems-thinking approach. According to Sterman (2000) there are three main features that characterize the bullwhip effect and are prevalent in SCs: oscillation, amplification, and phase lag. The amplification and oscillation imply that the amplitude of fluctuations increases as they propagate from customer to supplier. The time lag means that each upstream stage in a SC tends to lag behind its immediate customer.

The bullwhip effect poses substantial operational risks especially for upstream companies such as the semiconductor and chemical suppliers in the automotive SC. Due to their upstream position, changes in demand at the downstream level, e.g., end market demand for cars at the original equipment manufacturer (OEM) level, amplify upstream and lead to high demand variability. Due to its upstream position, the magnitude of the bullwhip effect on the semiconductor industry is significant (Mönch et al. 2018). Additionally, long lead times and positively correlated demand further increase amplification for the semiconductor industry (Chen & Lee 2012). These features make managing the semiconductor SC a challenging task. Existing literature such as the work from Ehm & Ponsignon (2012) focuses on the bullwhip effect in the semiconductor industry and approaches to manage its effect at the E2E SC level. Fransoo and Udenio (2020) describe the bumpy road ahead of the SCs when exiting the COVID-19 crisis. They outline that during COVID-19 lockdowns, demand for cars dropped significantly which caused significant upstream inventory build-up. In the summer of 2020, demand for cars increased, inventories decrease, which resulted in severe shortages for upstream suppliers like the semiconductors companies.

2.3 End-to-End Supply Chain Simulations

According to Terzi and Cavalieri (2004) simulation is one of the most applicable methods for modelling complex systems. Therefore, E2E SC simulation has been widely employed to analyze multi-echelon SC behavior. Research in E2E SCs has been applied to analyze different aspects such as the analysis of bullwhip effects in SCs, inventory management, SC network design, SC risk management and SC performance where different simulation methods were used in each of these areas. A profound understanding of the SC and modelling techniques is necessary for modelling a multi-echelon SC (Chilmon & Tipi 2020). Amongst other simulation methods, system dynamics (SD) simulation has been applied to different use cases. These studies usually focus on causal loop diagrams and control theoretic aspects.

Research around bullwhip effects in E2E SCs is diverse. Dominguez et al. (2014) focus their work on mitigating bullwhip effects in a multi-echelon SC. They conclude that collaboration and smoothing behavior can decrease demand amplification. Effects of inventory management strategies like vendor-managed inventory (VMI) on the bullwhip has been analyzed as well (Afridi et al. 2020). VMI in multi-echelon SCs can eliminate some components of the bullwhip effect (Disney & Towill 2003). Hussain and Drake (2011) investigate the effect of batching on the bullwhip effect for E2E SCs with a SD model and conclude that a smaller batch size does not reduce demand amplification. Wangphanich et al. (2010) develop a SD model to analyze bullwhip effects in a multi-stage SC with multiple products in a beverage company. Their multi-echelon SD simulation approach quantifies existing bullwhip effects and reduces their magnitude. The multi-echelon SD study of Pierreval et al. (2007) is applied to the automotive industry. They highlight that long or medium term decisions need a macroscopic view. Udenio et al. (2015) develop a SD model for analyzing bullwhip effects for different E2E SC settings and apply their model to a major chemical company. Their model builds a structure for each echelon of the E2E SC including delivery, production, forecasting and ordering aspects. The SD structure allows to track each of these components continuously. The authors conclude that destocking during a crisis enhances demand amplification.

3 METHODOLOGY

As presented in the previous section, several studies have investigated possibilities to simulate E2E SCs. After our study is classified in terms of existing simulation techniques and simulation approaches for the semiconductor industry, this section also introduces the methodological approach of the simulation, the SC setup and parameter setting.

3.1 Simulation Approach

Deciding on the right abstraction level is crucial. In general, three different simulation methods can be considered: while discrete-event and agent-based simulation can be applied for lower abstraction levels, SD modeling suits simulations with a higher degree of abstraction level (Grigoryev 2018). Fowler et al. (2015) provide several aggregation levels for simulation models in the semiconductor industry. E2E SC models, which are on the highest aggregation level, may focus on the interaction between different companies and the delivery of goods. Yuan and Ponsignon (2014) describe a use case for E2E SCs in the interaction between customers, manufacturers, and suppliers. This study has the purpose of investigating dynamics along an automotive semiconductor SC, and therefore focuses on the interaction and signal propagation upstream and downstream. We follow an E2E simulation approach as described in Yuan and Ponsignon (2014). Due to the high abstraction level we implement a SD approach. In our study, the system is the E2E SC comprising several actors. The development of the simulation model follows the framework proposed by Banks (2005). After formulating the problem and the desired outcome, relevant data was collected. Then the SD model was implemented and verified in AnyLogic 8.

3.2 Simulation Setup

We base our mathematical model for the SD approach on the book by Sterman (2000) and the work published by Udenio et al. (2015) and extend it with insights on inventory levels, capacity, and backlog levels instead of focusing on destocking behavior and pure demand prediction. Additional semiconductor specific requirements such as the long lead/cycle time and tight capacity restrictions are considered as well. The overall SD approach models a multi-echelon SC with N= (1, …, j) number of echelons, where 1 is the most downstream, and j the most upstream SC partner. Each echelon n receives and propagates an order signal and receives and sends a material flow (see Figure 1). First, the incoming demand signal at echelon n is provided by the downstream SC partner n-1. After demand signal O_{n-1} has been processed, order signal O_n is propagated upstream. Second, the incoming material M_n is processed in the echelon structure and sent as M_{n-1} to the downstream echelon. Each of the echelons consists of the same SD configuration extending the model described in Udenio et al. (2015) with additional capacity consideration and non-linear inventory management.

Five main parts shape the structure of each echelon: the delivery area modelling the material flow sent to the customer and backlog levels, the production area controlling the production amount and stock levels, the order and forecasting area processing incoming customer orders, regulating forecasting and considering the supply line of the respective echelon, and the capacity area ensuring production does not exceed capacity level.

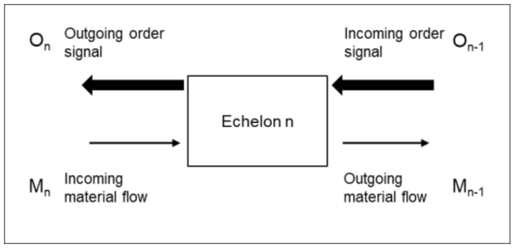

Figure 1: Conceptual overview echelon structure

Overall, the parameters used in the simulation model can be distinguished into behavioral and structural parameters. Behavioral parameters include the forecast adjustment time (FAT), which determines to what extent changes in the incoming demand signal influence the sales forecast, and the adjustment of the desired inventory level according to changes in the received order signal with the inventory adjustment time (IAT). High values for these reflect stronger smoothing in the forecast, and a more hesitant adjustment of the inventory level for the FAT and IAT respectively. Structural parameters such as the production time, leadtime and desired inventory coverage (DIC) are modelled as a delay function from the production to the inventory, as the amount of time from placing the order to receiving the product, and default stock level at the beginning of each simulation run, respectively. SD models are created by stock and flow elements, parameters and dynamics variables. The stock elements track the state of a component and changes its value continuously over time according to the given in- and outflow. Dynamic variables consist of functions and define intermediate states, while parameters define constant definitions. An overview of all relevant structural elements of the SD model developed in this study is shown in Appendix A. For a detailed introduction to and an extensive explanation of systems thinking and SD simulation the reader is referred to Sterman (2000).

The mathematical model aggregates all available products to one demand signal. This could lead to the situation where, despite a high aggregated inventory level, one of the items may not have a sufficient inventory level, and therefore not be directly available for shipment. To cope with this product aggregation assumption, Sterman (2000) defines a non-linear order fulfillment ratio (OFR). For the SC of this study, a semiconductor-specific non-linear OFR shape is developed through qualitative expert interviews and internal data for the semiconductor echelon. The maximum delivery rate (MSR) describes the ability to fulfill orders according to the current inventory level. The desired delivery rate (DDR) corresponds to the current demand signal from the downstream echelon, hence, describes how much should be delivered to the respective customer. For the linear relationship the following is assumed: given an inventory level of ten, hence, both the maximum delivery ratio and the desired delivery rate equal ten; in conclusion the ratio is one and the OFR 100%. Compared to the OFR shape presented in literature (Sterman, 2000), the developed semiconductor OFR is continuously lower, due to high product variety. An illustration of these two shapes and the linear relationship is shown in Figure 2.

3.3 Supply Chain Setup and Parameter Setting

The simulation model consists of several SC partners. The SC network design follows the structure explained in the previous section. The overall SC setup is an adapted version from a representation of a semiconductor SC in Forster (2013), where the authors model the SC as silicon supplier, wafer producer, semiconductor manufacturer and the original equipment manufacturer (OEM). The SC in this study models five echelons: silicon supplier, semiconductor manufacturer, Tier-2 supplier, Tier-1 supplier, and the OEM.

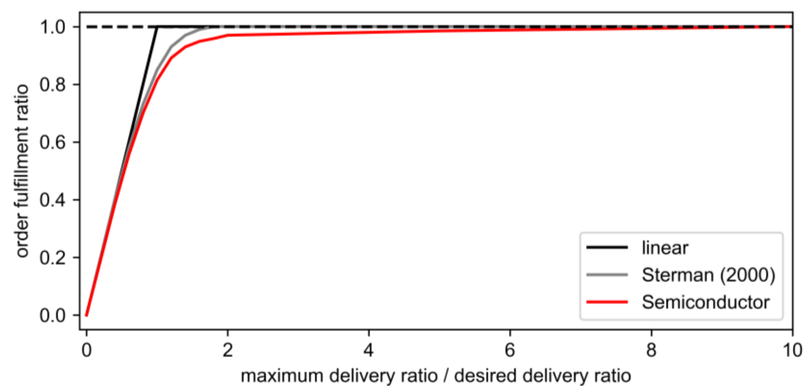

Figure 2: Order fulfillment ratio

The order signal to the most downstream echelon - the OEM - is the historic end market demand signal for global light vehicle sales, hence, an exogenous factor to the simulation model in this study. This demand signal then propagates through the SC from the OEM to the Tier-1 supplier, the Tier-2 supplier, and eventually up to the semiconductor manufacturer. The semiconductor echelon receives the material from the silicon supplier. This most upstream echelon, i.e., the silicon supplier, is assumed to have infinite supply. The semiconductor echelon manufactures the products, e.g., chips, and ships it to the Tier-2 supplier, which further processes the chips to more aggregated components. The Tier-1 supplier receives these and delivers their finalized components to the OEM. In this example, the semiconductor echelon receives ordered material from the silicon supplier and manufactures integrated circuits, e.g., for radar sensors. The Tier-2 supplier crafts whole components, e.g., radar sensors. The Tier-1 supplier then aggregates components, e.g., to an advanced driver assistance system. Finally, the OEM integrates this component into the car, i.e., the final product for the end market. At each of these echelons, the demand is aggregated on a global level, e.g., the demand from Tier-2 supplier to semiconductor echelon equals the global demand for chips. We measure in million car equivalents. An illustration of this SC setup can be seen in Figure 3.

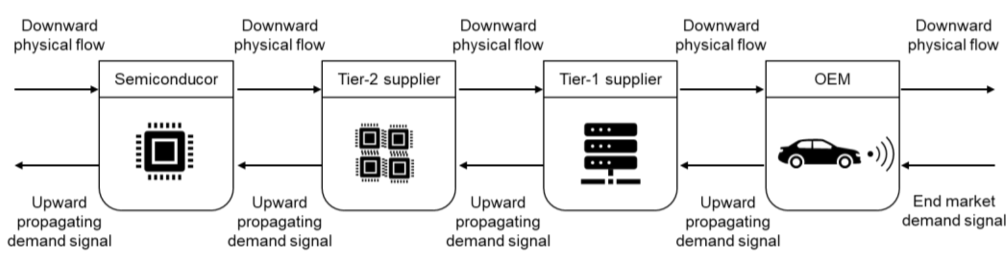

Figure 3: Supply chain setup for the case study

Validation and verification ensure that the model represents true behavior to the desired extent and increase credibility. The structural parameters have been defined through expert interviews; the behavioral parameters have been determined through a calibration experiment in AnyLogic 8, which minimizes the cumulative sum of squared errors between the historical and predicted incoming demand signal at the semiconductor echelon. According to Banks (2005) this model calibration leads to validity if the output of the model replicates the real system to the desired extent. In particular, historical data of the end market demand signal and the received demand signal at a semiconductor manufacturer supported calibration efforts for the behavioral parameters of the model, hence, follows a similar validation approach as described in Udenio et al. (2015). The results are additionally verified in the simulation tool and with qualitative expert knowledge to ensure the model is built correctly.

4 RESULTS COVID-19 CASE STUDY

The following section will provide the overall SC setup, i.e., the considered echelons, for the case study, and the observed results from the simulation and the sensitivity analysis. As part of this study, the global light vehicle sales market was smoothed with a three week moving average enabling the model to focus on the overall dynamics and to reduce oscillation. This data then determines the end market demand over time during the simulation run, which dropped more than a third during the beginning of the crisis and quickly recovered (LMC Automotive 2020). As Figure 4 (1) shows, this drop begins after a warm up period of 30 weeks and catches up with the initial demand more than a year later. This scenario, from now on referred to as the pandemic scenario, is analyzed in the following. The model considers not only the end market demand, but also extends the dynamics with the growth of electric content per car. For the scope of this model and due to the aggregation to car equivalent units, the electric content is assumed to be constant at 4% per annum. Higher growth rates lead to an even more challenging situation. Four aspects of the simulation will be of particular interest for the result exploration and analysis. First, the amplification of the demand signal due to the upstream position of semiconductor manufacturers. Second, the inventory levels to understand possible product shortages. Third, capacity management and loading for additional insights into the simulation result. Fourth, existing backlog levels will be discussed. Figure 4 displays the simulation results for each of these aspects. All of these are modelled as so-called SD stock elements (see stock elements in Appendix A).

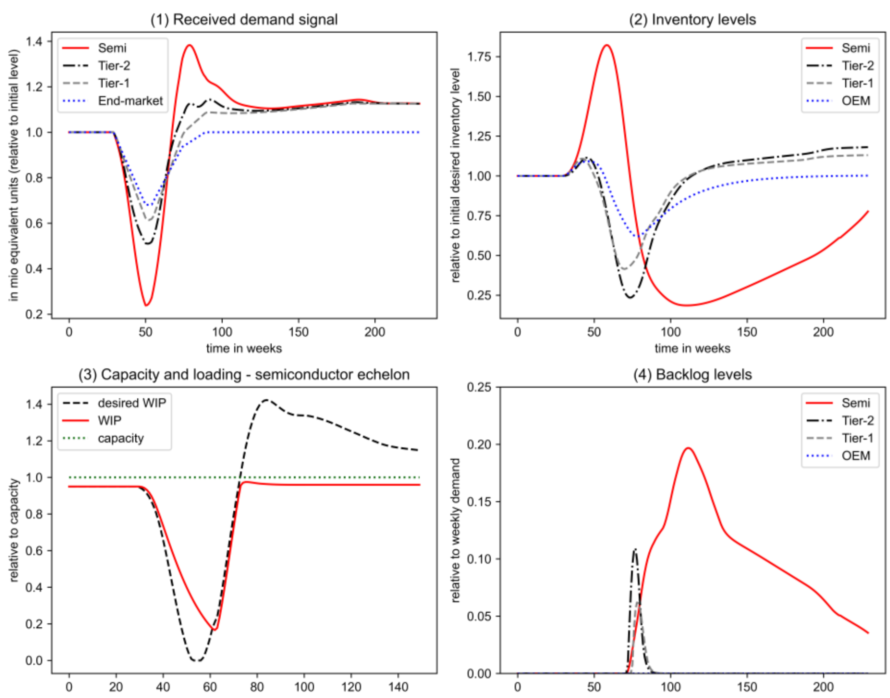

Figure 4: Results of the pandemic scenario – demand amplification, capacity and loading, inventory levels and backlog levels

Figure 4 (1) shows the incoming demand signal from the respective downstream echelon relative to the pre-crisis level. When the demand drop in the end market reached its minimum in March/April 2020 with a drop of more than a third, the drop for the semiconductor manufacturers was at least double the magnitude. The amplification of the change in demand increases upstream, and the semiconductor industry faces the highest amplification ratio. Therefore, the results of the simulation display the bullwhip effect along an exemplary semiconductor SC. While the incoming demand signal for the OEM, i.e., the end market demand, is still below 100% at week 80, the semiconductor industry receives already around 1.4 times the pre-crisis level. Consequently, the semiconductor manufacturers are in a challenging position due to the demand signal amplification in combination with the upstream position in the SC and the long cycle times. Relative to the desired inventory level, each echelon faces the problem of higher stocks than desired in the beginning of the crisis due to the cancellation of orders and lower end market demand. As a cause of the long cycle time for the semiconductor production, the inventory of the semiconductor echelon peaks later and much higher as the inventory is further filled with finished goods resulting from the complex semiconductor manufacturing process.

The work-in-process (WIP) at the semiconductor echelon cannot be adapted spontaneously. While the desired WIP drops quickly, the actual adaptation to the desired WIP level (dWIP), i.e., loading, takes longer. During the recovery phase, the capacity of the semiconductor echelon is insufficient with regard to the amplified demand signal, due to the inability to increase capacity quickly enough. Moreover, building additional production capacity for semiconductors is a capital intensive, long term decision and cannot be compensated through additional shifts as the production lines work up to 24/7 already. In conclusion, the insufficient capacity slows the recovery of the inventory level for semiconductors. An illustration of these dynamics can be found in Figures 4 (2) and (3).

As a consequence of the capacity restriction, not only the semiconductor manufacturer runs into backlog, hence, cannot directly fulfill incoming orders, but also Tier-2 and Tier-1 suppliers. From the end of December 2020 until the second quarter of 2021, the simulation model predicts a chip shortage along the SC. The backlog of the Tier-1 supplier towards the OEM is especially interesting as it was covered in the news as a global chip shortage (Inagaki et al. 2021). The backlog level peaks increase going upstream in the SC (Figure 4 (4)). The maximum backlog level is around 7% of the weekly demand for the Tier-1 supplier. The Tier-2 supplier and semiconductor manufacturer echelon have to recover from a backlog about three times as large as the respective downstream SC partner. Contrary to the rest of the SC, the backlog level of the semiconductor echelon in this simulation remains greater than zero for a longer period of time. This can be explained by the non-linear order fulfillment ratio which limits the flexibility in the order fulfillment if the stock level is not sufficiently high. Each of the components shown in Figure 4 are also summarized in Appendix A.

The following provides an analysis of two components of the simulation model. First, the variation of the DIC of the semiconductor manufacturers and its effect on backlog levels. Second, the adaptation of the FAT of several echelons to investigate the influence of the forecasting behavior on the SC performance. The analysis of the initial inventory level, i.e. DIC, of the semiconductor echelon can be seen in Figure 5 (1). Compared to the base case of the DIC at the semiconductor level, an increase of 5% and 10% reduces the chip shortage towards the Tier-2 supplier. However, this excess inventory leads to a significant increase of the inventory level for the semiconductor echelon during the drop. Figure 5 (2) displays the backlog for all echelons with the 10% increase scenario in the DIC at the semiconductor echelon. The results show that despite this adaptation, other SC members, except the OEM, still show backlogs greater than 0 – compare Figure 4 (4) and Figure 5 (2). Hence, this structural adaptation of one echelon is insufficient.

To investigate the influence of the behavior of other echelons on the SC performance, the following analyses the effect of an adapted forecasting behavior. In particular, a higher FAT describes a behavior where a change in the incoming demand signal is smoothed stronger. Figure 5 (3) displays the model result for the case that the Tier-1, Tier-2 and the OEM are doubling their FAT. The results show a significant decrease of the backlog not only for the semiconductor echelon, but this time also for the Tier-2 and Tier-1 supplier. The Tier-2 supplier faces no chip shortage anymore and the Tier-1 supplier less than 50% of the initial level (compare Figure 4 (4) and Figure 5 (3)). The reduction in the backlog level for several echelons reflects the value of coordination and collaboration efforts.

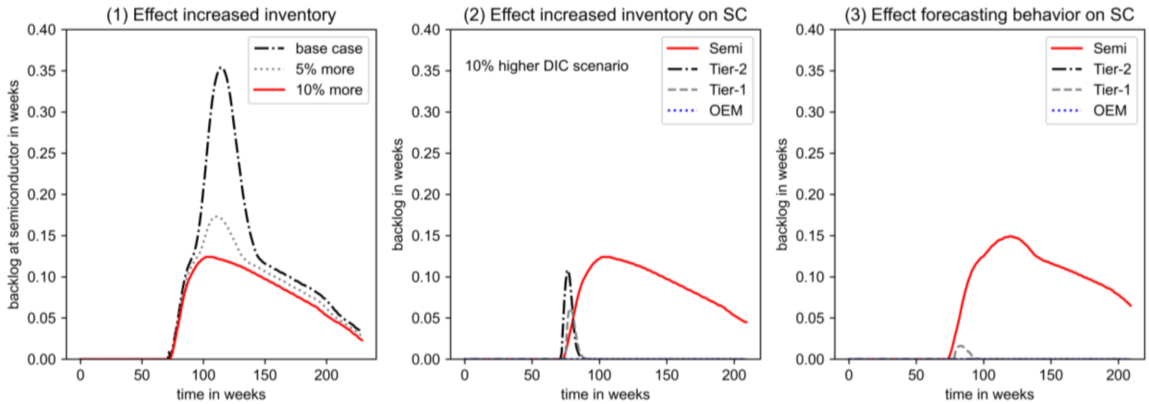

Figure 5: Scenario analysis of inventory level and forecast adjustment policies

5 CONCLUSION AND MANAGERIAL INSIGHTS

The simulation model represents the overall dynamics of an exemplary automotive semiconductor SC. As the simulation results show, the consequence of the harsh drop during the crisis is a chip shortage during market recovery. The results imply that the amplitude of demand amplification increases upstream the SC. Hence, this part of the SC suffers the most from end market demand disruption. To not bear the whole risk of the SC, semiconductor manufacturers also need to react upon amplified order behavior of downstream SC partners. Restoring the equilibrium state simply takes longer due to the long cycle times, the inability to adapt the WIP quickly, and the capacity restriction for the semiconductor manufacturers. Within the scope of this study, a higher inventory level can reduce the overall chip shortage during market recovery, but leads to a higher business and scrap risk for semiconductor manufacturers due to short product lifecycles. Incoming order signals higher than the actual desired level further complicate production resource allocation for semiconductor manufacturers. The results in Figure 5 suggest that each echelon can contribute to mitigating the bullwhip effect. Especially nervous forecast adjustment should be avoided as these adaptations propagate through the SC and are incompatible with the long lead and cycle times of semiconductor manufacturers. As the model results show, a smoother forecast adjustment is not only beneficial for this echelon, but also for other SC partners. This points out the value of collaboration and information sharing among SC partners.

Closer collaboration among SC actors is a crucial factor to master demand disruptions and its implications on inventory and backlog levels at the individual echelon level and for the whole SC. Behavioral coordination regarding forecasting and inventory management policies represent a promising future direction. The simulation model can be used as an automotive semiconductor SC reference model, which evaluates not only the demand amplification, but also critical components such as inventory and backlog levels and capacity allocation per echelon. Hence, providing the possibility for further discussion on improved collaboration and coordination among echelons and implications for each of the SC members.

A RELEVANT STRUCTURAL ELEMENTS OF THE SIMULATION MODEL

Structural element	Explanation	Dimension	Source of information
Stock elements			
$backlog_n$	Backlog at echelon n	Units	Endogenous
WIP_n	Work-in-process at echelon n	Units	Endogenous
$inventory_n$	Inventory level at echelon n	Units	Endogenous
$capacity_n$	Available capacity level at echelon n	Units	Endogenous
Parameters			
DIC_n	Desired inventory coverage at echelon n	Weeks	From interviews
IAT_n	Inventory adjustment time at echelon n	Weeks	Parameter calibration
FAT_n	Forecast adjustment time at echelon n	Weeks	Parameter calibration
Dynamic variables			
DDR_n	Desired delivery rate at echelon n	Units/week	Endogenous
OFR	Delivery ratio for order fulfillment	Dimensionless	Endogenous
MSR_n	Maximum delivery rate at echelon n	Units/week	Endogenous
$dWIP_n$	Desired WIP level at echelon n	Units/week	Endogenous
Flow elements			
O_n	Order rate placed by echelon n	Units/week	Endogenous
O_{n-1}	Customer order rate from echelon n-1	Units/week	Endogenous
M_n	Incoming material flow to echelon n	Units/week	Endogenous
M_{n-1}	Outgoing material flow to echelon n-1	Units/week	Endogenous

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AUTHOR BIOGRAPHIES

FRIEDRICH-MAXIMILIAN JAENICHEN is a double degree Master student in Management and Technology at the Technical University of Munich (TUM) and in Strategic Management at HEC Paris. He obtained a Bachelor of Science from TUM in Management and Technology and works in the Supply Chain Innovation department at Infineon Technologies. His email address is maximilian.jaenichen@tum.de.

CHRISTINA JOHANNA LIEPOLD is a PhD student and Research Assistant at the Professorship of Operations and Supply Chain Management at TUM. Previously, she completed the Master and Bachelor of Science in Management and Technology at TUM with a research stay at CIRRELT in Montréal, Canada, during her Master's Thesis. Her email address is christina.liepold@tum.de.

ABDELGAFAR ISMAIL MOHAMMED HAMED is a Supply Chain Expert in the Supply Chain Innovation department at Infineon Technologies. He has a Master of Science in Environmental Engineering from the Polytechnic University of Milan. He leads the Supply Chain Simulation within the Supply Chain Innovation department at Infineon. His email address is abdelgafar.ismail@Infineon.com.

CHRISTIAN JAMES MARTENS is a Chemical Engineering Master student at TUM with concentrations in Nanoprocess Engineering and Control of Dynamical Systems. He completed his Bachelor of Science in Chemical Engineering at the University of California San Diego. He works in the Supply Chain Innovation department at Infineon Technologies. His email is ChristianJames.Martens@infineon.com.

DR. ING. VOLKER DÖRRSAM is a Senior Director leading the supply chain excellence and digitalization team at the Automotive Division of Infineon Technologies. He has a diploma in Industrial Engineering as well as as Ph.D. in Mechanical Engineering from the Karlsruhe Institute of Technology (KIT). His email address is volker.doerrsam@infineon.com.

HANS EHM is Senior Principal Engineer Supply Chain of Infineon Technologies AG. He received his M.S. in Mechanical Engineering from Oregon State University in 1985. Since one decade he is heading the Supply Chain Innovation department of Infineon Technologies AG. His email address is Hans.Ehm@infineon.com.