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Simulating the COVID19-pandemic and its impact on the semiconductor supply chain: Enabling a supply chain risk management framework

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Abstract: COVID-19 pandemic, in the past 2 years, has affected all aspects of life, as well as businesses with different extents. The fifth wave, pushed by the omicron variant, seems to pave way to a new course of development. In this study we present a hybrid simulation modelling approach using agent-based simulation (AB) and system dynamics (SD). This hybrid model is used to evaluate the pandemic dynamics and its impact on the supply chain (SC) of a semiconductor company. We modelled the infection waves, governmental stringency values, and their impact on demand for several semiconductor applications. Additionally, we simulated vaccination, mutation factors and other recent developments of the pandemic. The results of the epidemiological model show that while the COVID-19 evolved in multiple waves, government restrictions and vaccinations are keys to control the spread of the virus. Moreover, the possible endemic nature of the pandemic fuels the importance of the continuation of our work, as this work will be the backbone of a SC risk management framework: resilient SCs need to be equipped with mitigation measures, to face future challenges. The results of the SC model suggest that mitigation of the COVID-19 disruption could be achieved by having high inventory and/or high global flexibility capacities.

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Keywords: Simulation modelling, system dynamics, semiconductor supply chain, supply chain disruption, supply chain, COVID-19

1. INTRODUCTION

The pandemic caused by the Coronavirus disease 2019 which is caused by SARS-CoV-2 (COVID-19) can be categorized as a black swan disruption, meaning a low frequency, high impact event (Simchi-Levi et al., 2015). The disturbances in the SC have been caused by governments issuing lockdowns and restrictions on social gatherings and day-to-day life to slow down the spread of COVID-19. These lockdowns have caused disruptions in several areas of the supply chain, namely in the areas of supply, demand, and logistics (Baveja et al., 2020; Ivanov, 2020). Moreover, due to the interconnectedness of the global SC, all echelons of a SC are affected by the disruption (Golan et al., 2020). At the beginning of the pandemic, inventory build-ups, especially in companies that are part of an extended SC, created significant problems. Reduced orders from companies downstream in the SC caused further irregularities along the SC due to decreased end consumer demand, a phenomenon called the bullwhip effect. Thus, the changed order behavior resulted in large fluctuations of orders that entailed stockouts and large inventory surpluses (Franso and Udenio, 2020). At the same time, however, global competition in the semiconductor industry has increased significantly, making an efficient SC more valuable to a semiconductor SC (Gupta et al., 2006).

Even before the COVID-19 pandemic, the semiconductor SC has been subject to long lead times of up to four months, volatile demand, and long reaction times due to the long setup times of machines. Due to these conditions, maintaining efficiency in the SC is one major challenge of the semiconductor SC (Chien et al., 2008; Ehm, Ponsignon, Kaufmann, 2011; Mönch et al., 2018). However, the most impactful change is associated with the changes in demand, as these changes will amplify with the bullwhip effect to the more upstream in a SC a company is located in (Balle et al., 2020; Lee et al., 1997). Due to these known effects on the demand, this paper focuses on estimating the demand impacts of the COVID-19 pandemic with focus on semiconductor applications.

To assess the impact of the COVID-19 pandemic on the semiconductor SC, a hybrid simulation model using SD and AB modelling is created which consists of two models. First, an epidemiological model, which is an extended SEIRHD model using SD modelling technique, is created, aiming to mimic the infectious development of a country by taking mutations, vaccinations, reinfection, and changed behavior towards stringency levels into consideration. Second, a SC model is created to assess the effect these epidemiological developments have on the SC where government restrictions...
influence the simulated demand disruption in the respective country. These government restrictions depend on the infectious development in the country. The Oxford Governmental Response Tracker introduced by Hale et al. (2021) is used to measure the stringency level in each country. To assess the impact of the pandemic on demand for several semiconductor applications, a use case from a semiconductor company in Germany is presented. As the scale of the disruption caused by the COVID-19 pandemic is not comparable with any disruptions that occurred before, the impacts this COVID-19 disruption has on the semiconductor SC is investigated.

2. METHODOLOGY

This section explains the methodology used to investigate the research questions in this paper. The methodology consists of the epidemiological model and the supply chain model. Both models were created using the Anylogic Software version 8. Simulation modelling allows a cost-efficient way of testing relationships, observing the interaction between different variables, identifying potential bottlenecks, and testing different hypotheses for feasibility while finding an optimized model. Lastly, simulation modelling allows observation of a model over a period at different speeds. As suggested by Currie et al. (2020), the simulation of infections, fatalities, and government actions like quarantine and social distancing requires a high level of abstraction, which makes SD the most suitable method to simulate the pandemic’s development.

2.1 Epidemiological Simulation Model

The most commonly used epidemiological model is the SIR model in its simplest version. There, susceptible people (S) become infectious (I) and after convalescence, recover (R). For the requirements of COVID-19 pandemic an extended version of the SIR model is used namely the SEIRHD (Susceptible, Infected, Recovered, Exposed, Hospitalized, and Dead) model adapted from (Ivorra et al., 2020, p.4) and includes several factors such as mutation flows and a vaccinated stock. The stocks and flows of the extended model are shown in Figure 1. In addition to vaccination and mutation flows, we assumed that after a certain period, one is no longer immune but at risk of being infected again as the flow between UDR and HR stocks is connected to the S stock as can be seen in Figure 1.

![Figure 1: The SEIRHD model (adapted from Ivorra et al., 2020, p.4)](image)

The relationship between the number of cases and stringency level was described in a table function created by correlation analyses which showed stringency increases as infections increase and decrease as they decrease. To standardize the measurement of government restrictions historic stringency values were taken from the Oxford COVID-19 Government response tracker, established by Hale et al. (2020). Data about infectious development is taken from Global Initiative on Sharing All Influenza Data, in short GISAID, and compared to the simulated data to ensure the accuracy of the available historical data.

One year after the pandemic started, vaccinations were also at the disposal of world governments to help controlling the spread of the pandemic. In this study we followed an approach similar to Feng et al. (2011). The model was adapted to include the vaccination parameters for the studied country. The parameters include: Initial date to begin vaccinating, delay of time for someone to be immune after receiving the required doses, the effectiveness of a particular vaccine being used in terms of reducing the likelihood of developing serious symptoms, the maximal capacity of the daily vaccine for the specific country, the percentage of acceptance among the population and the values that better fit a linear increment in the capacity of the daily vaccine. With this information, people were moved from the susceptible container to the vaccinated (V) one rather than being exposed or infected as shown in Figure 1. Vaccinations are not the same all the time thus different daily vaccination rates need to be simulated. Hence three different linear approximations were used which allow reducing the approximation error from 18.26% with a simple linear approximation to 3.86%. This only works until the expected vaccination capacity is reached. As the vaccination efficacy is reported to decrease by around 6% every two months for the vaccine BNT162b2; commonly referred to as BioNTech (Thomas et al., 2021) the model additionally implemented reinfection by creating a flow from V stock to S stock as shown in Figure 1.

For modelling, it is assumed that cumulative variants are dominant over the original COVID-19 infection, while the delta variant is dominant over all. To capture the spread of the mutation we created two additional flows from E to I stocks, and table functions for different spread scenarios. The data for these table functions were taken from the covSPECTRUM (2021) website, which gathers and visualizes data on mutation spread. To capture lockdown fatigue i.e., reduction of government stringency impact on cases and deaths, a country-specific reduction factor was incorporated. A table function was made with value 1 until a stringency condition is fulfilled, then a reduced value based on the reduction factor.

2.2 Supply Chain Simulation Model

The objective of our SC simulation is to assess the long-term impact COVID-19 has on KPIs such as stock development (at the Wafer, DieBank, Distribution Centre and consignment), backlog, and demand fulfillment. This involves assessing end-to-end governmental stringency impact on customers and suppliers, which requires a high abstraction level using SD, while AB modelling is deemed best to convey data between SC nodes, i.e., supplier, frontend, backend, customer, and flexibility nodes. Our multi-echelon SC model is adapted from Kienzl (2020) so this paper mainly describes extensions made such as stock management and noise. It models orders incoming, O_{i-1}, outgoing, O_i, and material input, M_i, and output, M_{i+1}, O_{i+1} from a downstream supply chain partner as...
processed in echelon I and sent upstream as $O_s$ and $M_i$ delivered by an upstream partner is processed and output downstream as $M_{s1}$ as shown in figure 2.

$$O_i: \text{Outgoing Order amount} \quad O_{i-1}: \text{Incoming Order amount}$$

$$M_i: \text{Input Material} \quad M_{i-1}: \text{Output Material}$$

Figure 2: Overview of the simulation modeling approach

Important flows in the echelons are the production and inventory flow, which calculates the amount delivered to the next node using factors like $M_i$, stock level, transit time, production rate, and the forecast flow and stock management loop, which predicts sales using forecast vs $O_i$, calculates desired stock level, $DS_i$, using initial demand and lead time, then places a readjustment order when there is unbalance between stock flow and $DS_i$, and lastly $O_i$ is passed upstream. Furthermore, a backlog flow calculates the difference between $O_i$ and delivery rates while a flexibility element transfers the backlog to a flexible plant, and a demand adjustment loop adjusts demand to pandemic impacts considering stringency change, revenue change, a product-specific impact of demand strength factor, normally distributed white noise, and seasonal pink noise which counters volatile ordering behavior. The epidemiological model in 2.1 is the input to the customer demand adjustment loop. The overall SC structure is shown in Figure 3.

Figure 3: Supply chain simulation model

2.3 Demand Impacts

The significant impact of government stringency on demand for products indicates a need to capture demand effects and this is done by considering national GDP as an economic indicator for the customer agent. The GDP data are obtained from OECD (2021) and FRED (2021). Correlation between monthly GDP and stringency is analyzed and found to be negative meaning that higher stringency levels correspond to lower monthly GDP. This is used to create a table function to simulate COVID-19 pandemic impact on demand. The length of higher stringency levels and their larger effect on GDP decrease and the fact that impact of stringency on GDP decreases as pandemic duration increases are considered in the simulation. A second correlation analysis between quarterly GDP and quarterly revenue of a semiconductor company shows a weaker positive relationship between sales and quarterly GDP. Based on this finding a country specific GDP growth rate is used to indicate sales growth rate at the use case company and a table function is created showing change in GDP vs change in revenue. To validate the results of the demand impacts simulation they are compared to the historical monthly demand data of different product clusters 1 and 2, from the use case company. It is shown that the change in stringency impact on demand can be recreated.

3. RESULTS OF THE EPIDEMIOLOGICAL MODEL

The epidemiological simulation model is run with the start date being 01.01.2020, which refers to day one in the results. The model can capture the historical waves of infection and predicts that cases will continue to rise in the future in small waves until the end of the simulation period. These results are in line with predictions made by several health institutions and epidemiologists that do not expect the virus to stop spreading anytime soon; instead, they expect seasonal infection peaks as described by Telenti et al. (2021) and likely an endemic. However, it is also expected that hospitalizations and death numbers decrease compared to the overall infection numbers as a result of the vaccination campaigns.

![Epidemiological results of cumulative cases in Germany](image)

Figure 4: Epidemiological results of cumulative cases in Germany

The results of the epidemiological simulation additionally show that until day 451, the original COVID-19 infection is the dominant infection. From day 451 to day 560, the general variant is dominant. From day 561 onwards, the delta variant is the most dominant one, implying that the virus's transmissibility increases from day 561 onwards, as visualized in Figure 4. Furthermore, the COVID-19 infection numbers with the respective mutants can be simulated and are shown in Figure 5.

![Share of COVID-19 variants](image)

Figure 5: Share of COVID-19 variants
The estimated hidden share of COVID-19 infections is also depicted, which indicates how many cases can be found in the population. These results, however, are hard to verify, as little research has been done on this topic. Figure 5 shows the cumulative variant spread which clearly shows that delta variant drove the infections significantly compared to the previous variants.

Figure 6: Cumulative share of COVID-19 variants

4. RESULTS OF THE SUPPLY CHAIN MODEL

To assess how the demand impact caused by the COVID-19 pandemic impacts the SC, the same set of scenarios is created for the two different product lines, cluster 1 and cluster 2, and investigated. The simulation results are then used to investigate the overall dynamics of the SC. The simulated scenarios can be divided into three different categories: lean SC, redundant SC, and flexible SC. In each general category, three different scenarios are simulated. In both the lean and the redundant SC scenario, the desired stock level is varied, while in the flexibility scenario, the capacity at the flexible backend is varied. The simulation was run for two different products to assess whether the impacts on the SC differ on the reduction of demand that happens during the initial lockdown period, as this is more profound in cluster 1 than in cluster 2.

The initial demand for cluster 1 and cluster 2 is set at the observed average demand for the last 12 months before the simulation period, so it is the average demand for the year 2019. The minimum capacity of the flexible backend was calculated using the approach presented in Kienzl (2020). The high capacity scenario doubled this minimum capacity, and the very high flexible backend capacity has quadrupled the capacity at the backend. The variation of capacity at the backend allows investigating the impact of higher available flexible capacity at the backend on the overall dynamics of the SC. To assess whether different SC impacts occur when products are affected differently in demand, the same scenario settings are run for cluster 2, with the only difference in the settings being the initial demand data and the impact. For cluster 2, a lower demand impact by the pandemic is assumed to have only half the demand impact from the calculated demand effects, while the demand impact for cluster 1 is higher and follows the demand impacts exactly. The results of the three scenarios are discussed in details in the following subsections.

4.1 Lean SC scenario

For the lean SC, the stock scenario shows effects of the bullwhip effect, namely oscillation, phase lag, and amplification. The results of the lean SC scenario are presented in Figure 6. First, the stock levels show fluctuation over the simulated time. Second, these fluctuations are most prominent in the wafer stock, which refers to the stock that is furthest away (most upstream) from the customer. While in the consignment center, which is closest to the customer, the fluctuations are not as visible. Thirdly, it is visible that the stock levels reach their peaks at different times, indicating the occurrence of time lags. While the effects observed in this SC simulation seem to indicate consequences of a ripple effect as described by Ivanov (2020), the primary concern in this paper is on changes in operational parameters, and the following possible imbalance of supply and demand. Thus, the effects of the pandemic disruption here refer to the bullwhip effect. The SC simulation only uses the customer's demand as input, the same effects are observed, as phase lag, oscillation, and amplification which can develop in the upstream SC. In the stock development graph depicted below, only the impacts of the pandemic on demand are considered, and thus the stock development levels cannot be directly compared to real stock data.

Figure 7: Results of lean SC scenario

In the initial phase of the lockdown demand at the customer decreases drastically, thus the distribution center's inventory levels are initially relatively high, and since demand is very low, the number of orders sent to upstream SC partners is also very low. However, since demand is projected to recover fast and higher orders are given to upstream SC partners, stock levels at the distribution center soon decrease. In the backlog levels at the backend, it can be seen that there is also a cyclical backlog development which is different in time from the cyclical development of the stock levels; additionally, backlog levels are very high. Lastly, the demand fulfillment shows that with lean SC, demand fulfillment will not be possible, it will drop cyclically at a similar time when backend backlog increases are highest as seen in Figure 6.
4.2 Redundant scenario

Next, the results of the redundant SC scenarios are analyzed. We varied the stock three times. Here, the scenario with the lowest stock level out of the three different scenarios analyzed still shows signs of the bullwhip effect, namely oscillation, phase lag, and amplification. The results of the redundant scenario are shown in Figure 7. The higher the stock level, the less pronounced these bullwhip effects are. Here it is visible that only the stock development in the die bank was affected, while the development of the consignment stock, distribution center, and wafer stock is not fluctuating. Demand fulfillment with redundant SC strategy is always possible, even when demand starts to increase at a high rate as demand recovers from the drop in demand caused by initial lockdowns of the pandemic. Backlog levels observed over the lean SC scenarios as well as over the redundant SC scenarios show that the higher the desired inventory level, the lower the backlog level at the backend will be.

4.3 Flexible SC scenario

Due to the drawbacks of very high stock in redundant SC, the flexible SC is analyzed. In the flexible SC scenarios, once backlog at the backend is created, this backlog is shifted to a flexible plant that produces the backlog as long as capacity is available. The results for cluster 1 in the stock level development do not show any signs of the bullwhip effect, as no oscillation, phase lag, and amplification can be found. The results of the flexible scenario are displayed in Figure 8. After demand impacts from the pandemic seem to normalize, the stock levels seem to remain relatively constant in the remaining simulated time frame. The different products cluster 1 and cluster 2 here gathered only slightly differing results. While for cluster 1, the stock developments for the flexible SC showed no fluctuation, the stock development for the same scenarios for cluster 2 showed fluctuations in the distribution center. However, these fluctuations are less intense than those observed in the lean supply chain scenario. While for all scenario runs, backlog levels at the backend still exist, they are significantly smaller than the backlog levels observed in the lean SC scenario. While the flexible SC allows keeping stock levels relatively low and does not accumulate as much backlog as the lean SC, the major disadvantage in this SC scenario is the longer cycle time it yields. The average cycle time of the SC is increased by the additional time incurred at the flexible backend.

5. CONCLUSION AND OUTLOOK

This paper, aimed to understand the dynamics of the COVID-19 pandemic. We studied how government restrictions, their length, infection numbers, mutations, and vaccinations impact demand for semiconductors. In Germany, it is found that the continuously appearing infection waves are linked to the spread of different mutations that are more transmissive than the original virus. Due to the country vaccination efforts, fewer people are infected with the virus. However, these vaccination efforts are offset in part by the increasing transmissibility of the mutations.

Furthermore, the results indicate that the lean supply chain is exposed to all of the consequences of an existing bullwhip effect, that can be caused by such a pandemic: oscillations, phase lags, and amplifications. These characteristics disappear in the redundant supply chain, as inventory levels are high enough to buffer the changes in demand along the supply chain. Moreover, these effects also appear less pronounced in a flexible supply chain. This enhances the importance of information sharing and trust among the SC members.
Since the beginning of 2022 the share of the omicron variant in the population (of infected) surpassed delta. In order to capture the dynamic of omicron, we will follow a similar path and keep working on the model, further analyze our simulations and work to create an adapted risk framework, in order to keep the SC a competitive advantage during times of uncertainty.

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