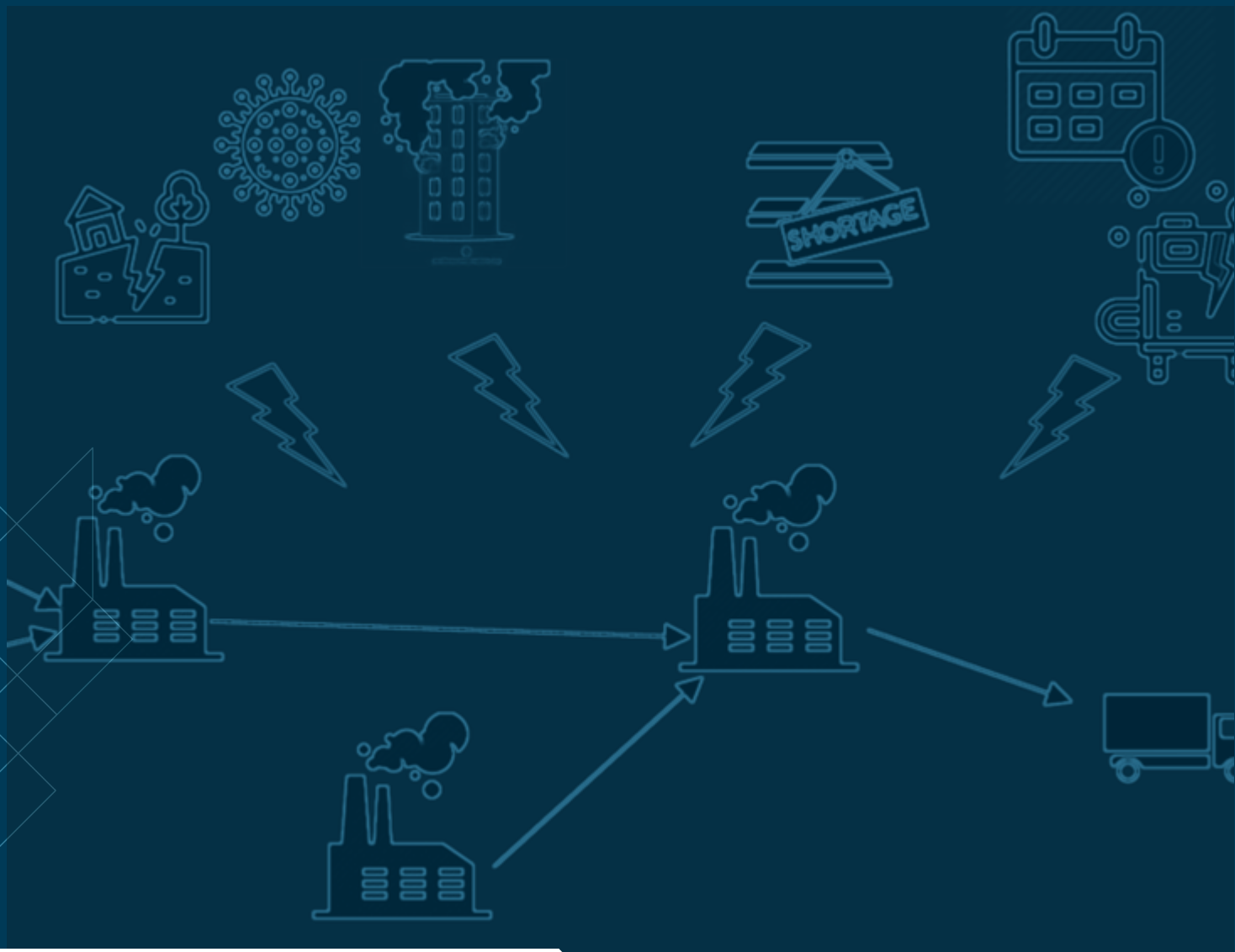
FINAL REPORT SEPT 2023

PROJECTNAME

EVIDENCE-BASED DISRUPTION MANAGEMENT

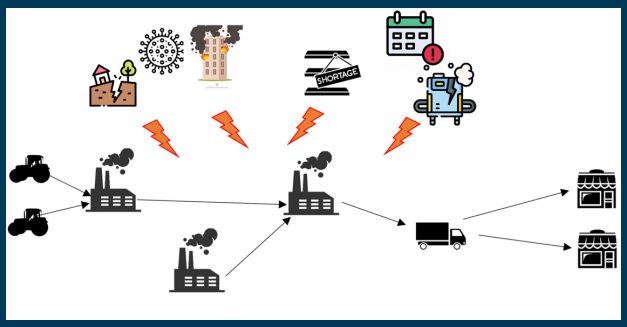
(EBDM)



TKI DINALOG
Dutch Institute for Advanced Logistics

SUMMARY

A crucial challenge for nowadays supply chain networks is represented by their resilience, intended as the capability of ensuring business continuity in presence of disruptive events. Given the high interdependencies among nodes within a network, strategies to mitigate disruption impact must consider not only a single firm, but the entire network. However, the development of strategies to enhance network resilience faces significant difficulties. Among them, a key factor often highlighted in literature is the lack of transparency within the chain. Indeed, usually different partners in a SC are only aware of their own function/products within the chain, while an overview of the overall chain, with corresponding dependencies among the nodes, is missing. This often results in a lot of uncertainty for the companies when it comes to react to disruptions.



To address this issue, this project developed novel methodologies and tools to allow companies to extract evidence-based insights on their supply chain networks, and to investigate how the related processes are interconnected. In particular, we introduced methodologies to allow companies to gain a better understanding of their supply-chain network, allowing them to investigate how their operational processes are interconnected with their partners in the supply chain. We investigated how this visualization can also support companies in understanding how the occurrence of disruptions propagate through a network and its impact on single nodes (firms) as well as on the overall network.
We focused on two granularity levels for the network visualization, i.e., the relationships (macro level) and the products (micro level). The first one is focused on the tiered relationships in the network; namely, it allows to visualize the downstream and upstream picture of the network. The second one is at a more fine-grained level, since it focuses on the flow of materials within companies related to their operational processes.

The developed tools and methodologies have been tested in collaboration with the involved companies, collecting evidence on how these insights led to a) improve network transparency, and b) supporting decisions via both financial and operational actions to recover from occurred disruptions. Furthermore, previously occurred disruptions on the built networks have been studied, to derive best practices in reaction and recovery strategies from which recommendations to face current disruption can be built. The obtained results shown the potential and the feasibility of the developed techniques to suport companies in reacting to network disruptions to mitigate their impact; at the same time, they also revelad that additional research is needed to overcome challenges related to the generalizability and scalability of the developed tools, as well as to challenges related to ensure the tool adoption by the targeted users.

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"THE RESEARCH WAS ABLE TO DERIVE VALUABLE INSIGHTS ON DISRUPTION PROPAGATION IN NETWORKS OF FIRMS"

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BACKGROUND

Disruption management is widely acknowledged as a critical aspect of supply chain (SC) management. Indeed, being prepared for and providing timely reaction to disruptions is essential to mitigate their impact on the business continuity of the firms in the chain. The subject has been extensively studied in literature, and several empirical studies have been conducted to investigate impact of disruptions and the corresponding mitigation strategies. Disruptions can be broadly categorized into two groups: Economy wide (large scale, e.g., Covid-19, GFC2008, etc) and Firm-specific (e.g., Boeing 737Max crashes, factory closures, etc). This project followed up research conducted by the TU/e team in previously funded Dinalog projects that looked at both the economy wide and firm specific disruptions. The DASCOVIMI project (funded April 2020) and the Cash Flow Harmonization (CFH) project (funded Dec 2017) have both provided us with interesting insights on disruption management at the firm level.

The CFH project looked at disruptions caused by operating cash flow volatilities at the firm level. The findings of this project show how firms should react (operational and financial actions) when they face such cash flow shocks for faster recovery. These actions have a substantial impact on the performance of the firm, thus highlighting the importance of taking the right action at the right time. The DASCOVIMI project was aimed at assessing the impact of Covid-19 on a set of Dutch companies. This project provided us with an extensive cause-effect diagram that can be used to analyze and act on issues a firm and/or its supply chain faces during an economy wide disruption. An issue that was frequently highlighted by the firms that participated in this project was the lack of transparency within the firms in their supply network. However, both these projects take a myopic view of a focal firm. Firms are not alone in facing disruptions – these shocks can impact all firms in their supply network. However, usually different partners in a SC are only aware of their own function/products within the chain; a general snapshot of the overall chain, with its related processes, describing both the single partners' roles and their interconnection (and dependencies) within the chain, is missing. Consequently, there is a lack of transparency in product and financial flows as well. Such lack of transparency often results in a lot of uncertainty for the companies when it comes to react to disruptions. Therefore, strategies to mitigate disruption impact must consider not only a single firm, but the entire network. This is a well-known gap in supply chain literature, and one that we focuse in this research.

CHALLENGE

The novelty of our research is twofold. First, we developed novel solutions to address the lack of transparency among supply chain partners, which often hampers the capability of firms to take informed decisions to react to disruptions. To this end, we developed data-driven analysis techniques able to exploit production data (e.g., BOMs, orders transactions, data from ERP and MRP systems) to gather data-driven insights on the analyzed network and visualize the overall supply chain network at micro level.
To achieve this goal, we investigated the application of process mining principles. This is a discipline aimed to discovery, analyze, and improve organization processes starting from data tracking process executions, thus allowing to investigate organization processes as they really occur within the organization.
The second element of novelty is the development of research methods to analyze disruptions not only at the level of single (focal) firms, like usually done in literature.

The main objectives of the project are listed below.

1. A buyer-supplier relationships networks over a set of supply chains affected by disruptions;
2. Prototype tools implementing novel evidence-based techniques to generate products flow network of a supply chain;
3. Qualitative and quantitative insights on the impact of past disruptions on single firms and the overall network, both in terms of financial performance and production related activities;
4. Prototype tools aimed at early-detection of disruptions;
5. Qualitative and quantitative insights on successful firms recovery actions.

PROJECT DESIGN

This project is a two-year industrial research project that included the scientific research by Eindhoven University of Technology (TU/e) in post-doctoral projects and Master thesis projects. The project entailed two parallel paths, a Top-Down (TD) approach that investigated financial management in the network, and a Bottom-Up (BU) approach what investigated the process and product management in the network.
The project related to the following innovation themes of Dinalog: i) Supply Chain Management, ii) Data-driven Logistics, iii) Customs and Trade.
The project hal been conducted in partnership with three private companies included in the consortium, namely ChainStock, Hilti AG and Neways. Other companies have been involved during the project through master these projects. The workpackages of the project are listed below.

1

ACTIVITY 1.1: ACQUIRING BOMS AND PROCESS MINING DATA

This activity collected and cleaned data related to companies supply chain processes, considering both internal processes and processes involving partners. Examples of data sources are, e.g., order transaction logs, inventory data, operational processes logs, production scheduling, products BOMs.
Deliverable: dataset

ACTIVITY 1.2: ACQUIRING SECONDARY DATA

For the macro level analysis, a lot of secondary data was required. The goal of this activity is to have access to multiple international economies from all sectors of the industry. In addition, we need to also construct a local database of disruptions that have been reported during the sample range. The following data sources has been aggregated in this activity:

a) Compustat (link): These databases have financial, statistical and market information on all active and inactive global companies. (this covers almost 99% of total world market capitalization)
b) Factset Supply Chain Relationships (link): This database exposes the supply chain relationships and connections of companies on a global level. This is the most important database because it will generate the supply networks for any focal firm.
c) Factset Shipping Transactions (link): This dataset maps the bills of lading from 1200 international ports with shipping transaction data. It contains the cargo content description, the departure and arrival ports as well as shipper and consignee relationship. This database is crucial to understand the operational impact of disruptions.
d) Deliverable: dataset

ACTIVITY 1.3: MINING AND MODELLING THE SUPPLY NETWORK

This activity brought in the resources from Activities 1.1 and 1.2. One of the first steps for managers in companies to understand the complex nature of the supply network is to be able to visualize it. We developed techniques to generate this network using evidence. We investigated how the network can be derived both using a TD and a BU approach. The TD approach makes use of public information of traded companies which make available the list of their tiers. While this is valuable information, it is only available for companies which choose to make this information public. Therefore, in this activity we also developed techniques to build the network in a BU approach, to overcome these issues, leveraging principles of process mining.
Deliverables: network analysis tools

2

ACTIVITY 2.1: DETECTING DISRUPTIONS AND ASSESSING THEIR IMPACT

The goal of this activity consised in developing techniques to detect and analyze disruptions within a single company and understanding the impact of these disruptions both on the company operational processes and on the network. To achieve these goals, we employed principles of process mining techniques, extending classic techniques to deal with SC challenges. The activity involved the following sub-tasks:

- Detect disruptions within company supply chain processes. First, the discovery of the "normal" flow of company supply-chain processes using process discovery techniques has been carried out. Once the normal flow has been defined, deviations from it can be detected and analyzed using outlier detection techniques.
- Assess disruption impact on single firm. Root cause analysis has been performed, together with an assessment of the impact of these disruptions on the firm capability to achieve its production/delivery goals.
  Deliverable: Ripple effect analysis methodology

ACTIVITY 2.2: MAPPING DISRUPTION IMPACTS ON SUPPLY NETWORKS

The goal of this activity is to understand the broad impact of different disruptions on supply networks and how they propagate through the firms in the network. This activity focused specifically on the macro level view, i.e., impacts on firm performance (both financial and operational) will be studied. This provided us with quantitative evidence on why firms should act when facing disruptions. Different types of disruptions have been studied during this activity – economy wide disruptions (that impact many firms) and firm specific disruptions (that impact a single firm in the network).
Deliverables:
- Impact on financial performance (RoS, RoA, liquidity, etc)
- Impact on operational performance (working capital, CCC, trade policies)
- Differential impact of geographic diversity in network (global vs local)
- Differential impact on downstream and upstream firms

3

ACTIVITY 3.1: EARLY WARNING SYSTEM DEVELOPMENT

This activity was aimed at developing an early-warning system to detect disruptions and to support mitigating actions. To this end, we developed predictive and prescriptive process-monitoring techniques.
Deliverable: Early warning system

4

ACTIVITY 4.1 DISRUPTION RECOVERY (OPERATIONAL ACTIONS)

This activity was aimed at analyzing companies processes in relation with their management of the disruption, to derive good practices and recommendations. Furthermore, we investigated the use of decision support tools implementing scenario analysis within SC processes to support managers in determining mitigating actions in relation to different disruption scenarios.
Deliverables:
- Evidence-based recommendation for disruption mitigations
- Scenario analysis tool.

4

ACTIVITY 4.2: DISRUPTION RECOVERY (STRATEGIC ACTIONS)

The goal of this activity is to identify successful disruption response actions from unsuccessful ones. Using the descriptive analytics from Activity 2.2, this activity encompassed two parts:

- Firm level: we split the firms into two groups – the first group has faster response and recovery from disruptions than the second. The actions taken by these firms must therefore be better, and these will be visible in their financial and operational performance metrics (working capital management, liquidity management).
- Similarly, we also grouped networks (a set of firms) that were resilient to or were unaffected by disruptions compared to others. Their collective actions can show how networks should behave when the entire chain will be affected.

Deliverables:

- Evidence based strategic actions for disruption response.
- Immediate disruption response measures
- Strategic supply network planning (building in redundancy and resilience)

5

ACTIVITY 5.1: RESEARCH DISSEMINATION

The goal of this activity consists in preparing dissemination material, organizing and attending workshops and publishing papers and reports to promote the dissemination of the results obtained through the research.

Deliverables:

- A report describing the activities performed, the results, and the lessons learned for each phase of the project, to be published on the Dinalog website.
- Demos to show and promote the prototype tools developed within the project.
- Workshop material, to discuss the findings of the research within the consortium members and the members of the Europeans Supply Chain Forum.
- 2 Research papers.

RESULTS

This project delivered novel qualitative and quantitative insights on the impact of past disruptions on single firms and the overall network, both in terms of financial performance and production related activities, as well as novel methodologies and tools to analyze these disruptions and mitigating their impact. From the single firm side, the project delivered methods to a) exploit production data (e.g., BOMs, orders transactions, data from ERP and MRP systems) to visualize the overall supply chain network at micro level; b) predicting delays in supply and support decision-making for mitigating actions; c) carry out scenarios analysis to determine mitigation strategies for disruptions leading to resource shortage. From the firm network perspective, the project developed research methods to analyze disruptions not only at the level of single (focal) firms but which consider the entire network and the relations among the different nodes.

Firms that have better visibility of the geographic diversity of their supply chain are better prepared to take nearshoring and reshoring decisions. These decisions can lead to significant reduction in CO2 emissions. Furthermore, with improved visibility and the disruption mitigation actions prescribed by this research, these firms will be able to build resilient supply networks. This has a direct relationship with the market value of these firms.

The project is directly related to the following innovation themes of Dinalog:

- Supply Chain Management: This project delivered tools and methods for analyzing disruptions at both the macro and micro level. Mapping and understanding the disruptions' propagation is fundamentally useful to supply chain managers.
- ICT & Provision of Information and Data driven Logistics: This project introduced novel techniques and software tools to visualize networks and connect them with operational processes.
- Customs and Trade: With the help of the supply network visualization tool, firms can identify specific geographical disruptions (tariffs, duties) that can impact their performance.

The project also contributed to new collaborations between TU/e and the involved companies, thus strenghtening the knowledge infrastructure. The developed tools have been implemented or are being currently implemented within the organizations. The results of the project have been published in research papers and master theses.

SOCIATAL OUTCOMES	
CO2 reduction	0%*
Cost reduction	€ 0*
Avoided transport kilometers	0
Modal shift ton kilometers	0

*) indirect savings only

SECTOR RESULTS	
Value creation	€ 0
Sustainable jobs created	€ 0
Companies reached	>6
SMEs reached	>0
Researchers/students currently working at companies	4

SCIENTIFIC OUTPUT	
Master theses / Bachelor theses	4
PhD promotions	0
Academic publications	2
Citations academic publicaties	0
Academic seminars, workshops, presentations etc. / Practicioner symposia, workshops, etc	1

An overview of the project results related to the different project phases can be found in the following sections.

SINGLE-FIRM LEVEL

Detecting disruptions and assessing their impact on the network

A supply chain disruption and its ripple effect can have a significant negative impact. In this research, we aim at developing technique to visualize the supply chain and analyze the ripple effect due to the Suez Canal disruptions on the operations of Dow. To this end, we implemented the research framework shown in Figure 1.

The first step is devoted to acquire sufficient domain knowledge to understand the case under examination. Firstly, meetings with experts were scheduled to understand what information the provided reports entail and what processes they represent. From that it was made clear which activities are executed in these processes and how those are represented in the reports, but also which time variables in the report are linked to these activities. Secondly, information was gained on how the shipments are tracked. Thirdly, information was gained on the vastness and complexity of the network. Fourthly, information is gathered on which variables may be affected by a delayed shipment and thus which can be used in the disruption analysis. Step 2 involved the collection, understanding and preparation of data on shipments, orders and inventory. In the third step, these data were manipulated to obtain an event log in a format suitable to apply process mining techniques. The event log for this research was constructed with the goal of storing each shipment in the data as a case. Meaning that each case executes multiple activities at a certain time at a certain place, and where each activity is thus represented as an event in the event log. The place of an event will be either the shipping plant or the receiving plant/customer.

Figure 1 Research framework for ripple analysis

Eventually, each event in the log will include information on the case it belongs to, the plant/customer the activity takes place, the timestamp of the activity, and the planned timestamp of the activity. From the event log, a process model has been extracted in step 4, which provided a visualization of the (business) processes within the supply chain network, which was validated by experts from Dow. The model obtained for the shipment activities is shown in Figure 2.

Figure 2 Process model of the shipment process.

Once the event log was constructed an outlier analysis using Interquartile range was conducted on the duration of each case. This provided an overview of different shipments which may be considered outliers, based on the durations of their activities. Once the outliers had been identified from the event log, using the IQR, it was determined which outliers could be connected to a disruptive event. From the gathered shipment delays a total of 8 cases were selected and analyzed for any impact.

A Causal Tree (shown in Figure 3) has been derived with Dow Experts to determine which variables were likely to be affected by the shipment delay. These are therefore analyzed for any unusual behavior, i.e. impacts, that might be caused by the shipment delay. Moreover, the analysis aims to link a shipment delay to a disruptive event to explain the cause of the delay.

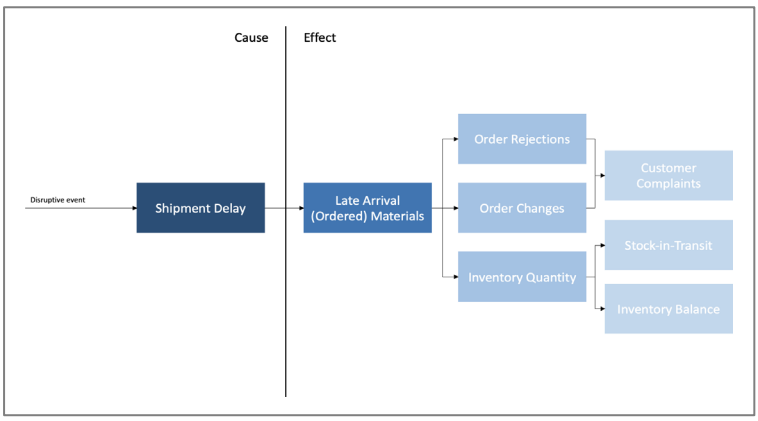


Figure 3 Causal Relations Tree

Table 1 Summary of the impacts found in the Results

Delay	Order Changes		Inventory	Customer Complaints		Order Rejections
	SP	RP	RP	SP	RP	RP
Shipment Delay 1	X	X	X	X	X	
Shipment Delay 2	X	X	X	X	X	
Shipment Delay 3	X	X			X	
Shipment Delay 4	X	X		X	X	
Shipment Delay 5	X	X		X	X	
Shipment Delay 6	X	X	X			
Shipment Delay 7		X	X			
Shipment Delay 8	X	X	X			

The results in Table 1 indicate that the shipping and receiving plant related to a case, i.e. shipment delay, may indeed be impacted by a delay. Moreover, the impacts that were found are partly in-line with the expectations that were derived from conversations with experts. Furthermore, the delays do not always cause the same impact. This is because the impact on the plant is dependent on many variables and a lot of these are unknown external variables. The analysis also shows that Dow Chem- ical already has some mitigation strategies in place, price change, for example. When low on a certain material Dow Chemical alters the price of that material to influence its demand.

Managerial Insights:

1. System is impacted by a disruption
   (a) Amount of shipment delays increase surrounding a disruptive event.
   (b) Order Change Reasons at the effected plants show an increase in order change reasons related to planning.
   (c) Customer Complaints often do not show an increase surrounding the time of a shipment delay, if so it is often a very small number.
   (d) No increase in Order Rejections can be found after a shipment delay.
   (e) System already seems to have some mitigation strategies in place that, in the analysis, seem to dampen some effects

2. A ripple effect can be seen; the effects are not isolated to either the shipping plant or receiving plant.

3. More research is required to fully understand the impacts.

Early warning system development

This research has been conducted at Bright Cape, a data consultancy company. Bright Cape has selected one of their clients as use case. The selected client is a global mining company, referred to as Company X for confidentiality reasons. Within Company X it is found that the on-time in full (OTIF) delivery rate is insufficient for purchased items from external suppliers. Since 40% of the purchased items is needed for maintenance operations, the insufficient OTIF rate has a negative impact on the maintenance completion of Company X. In particular, late delivered critical materials can disrupt their maintenance processes in the warehouses. To mitigate the effects of late deliveries, Company X calls the suppliers regarding the purchased items that are overdue. This process is called expediting. In order to improve the OTIF rate for purchased items, Company X wanted to be able to act more proactively and intervene before the purchased items are actually delivered too late. Moreover, they wanted to increase the impact of expediting on the OTIF rate by improving the decision making on which items to prioritize for expediting. To achieve this goal, we developed for Company X a framework able to i) predict the delivery date for purchased items, leveraging deep learning and process mining techniques, and ii) create a prescriptive model prioritizing purchased items from suppliers that need to be expedited for the day.

First, a business understanding phase was performed to investigate the purchase-to-pay (P2P) process and expedite process, as well as to determine the predictive and prescriptive task. Subsequently, a data understanding phase was executed to understand the available data and to determine possible input features for the prediction and prescriptive task. The results are shown in the table below.

Table 2: Results business & data understanding phase

Concept	Result
P2P process	Consists of these main steps: (1) create purchase requisition, (2) release purchase requisition, (3) create purchase order item, (4) release purchase order, (5) receive order confirmation, (6) vendor creates invoice, (7) receive advance shipment notice, (8) record goods receipt, (9) record invoice receipt, and (10) clear invoice
Prediction task	Predict the expected delivery date of purchased items. Model target: number of days between the contractual delivery date and goods receipt event (actual delivery date). The expected delivery date could then be obtained by adding this number of days to the contractual delivery date.
Selected input features predictive models	The P2P process activities, time since case start, time since last event, time since midnight, weekday, vendor, plant, BU, item, material/part number, OTIF of last year, PO lines per vendor, number of changes done to the delivery date, and number of days between PO creation and the contractual delivery date
Expedite process	Consists of determining the priority list for items to expedite. This is done by calculating an expedite score for all overdue items within the expedite dashboard of Compnay X in Celonis. The expedite score is calculated using a weighted scoring model, taking into account the factors: (1) material criticality, (2) stock versus non-stock, (3) supplier historical delivery performance, and (4) days overdue.
Prescriptive task	Generating a priority for expediting (expedite score), for each of the PO items, based upon the predicted delivery date and other relevant features.
Selected input features prescriptive model	Predicted delivery date, material criticality, stock versus non-stock, days overdue score, OTIF of last month, and OTIF of last year

Thereafter, we implemented a predictive process monitoring framework. This phase resulted in deploying a CNN model to predict the expected delivery date for items in the P2P process. To achieve this, the following phases were followed based upon the the Business Process Monitoring and Prediction Procedure Model (BPMP-PM).

- *Data Preparation*
  In order for the predictive models to understand the input data and use it effectively, the input data set had to be further preprocessed. First, the categorical features were encoded using one-hot encoding or embedding. Secondly, the numerical features were log-scaled to reduce skewness. Next, subsamples were created from the total dataset to be able to conduct experiments within reasonable time. Subsequently, the data in all subsamples and the total dataset was transformed into a prefix format to capture the sequential structure of activities in the log. To evaluate the models, the prefix data was split into a train, validation and test partition. Lastly, random over- and undersampling techniques were used to mitigate the effect of extreme and rare target values on predictive performance.

- *Model Selection & Implementation*
  Five neural network (NN) approaches were selected and subsequently implemented for the defined prediction task and were based on promising results in literature: the MLP, GCN, LSTM, CNN, and BIG-DGCNN. Besides, a Random Forest approach was added to these selected NN approaches. This approach investigated whether first classifying the extent to which a PO item would be delivered late/early with a RF followed by predicting the exact delivery date with the best performing NN would mitigate the negative effects on predictive performance due to extreme values for the target variable.

- *Evaluation*
  It could be concluded that the CNN was the best predictive model to implement for Company X when making a trade-off between prediction accuracy and computational efficiency. The CNN has a mean absolute prediction error (MAE) of 7.619 days for the prefixes in the test partition of the total dataset. This means that the predicted delivery date is on average 7.619 days earlier or later than the actual delivery date. The goal of Company X was to have a MAE of between 2 and 4 days. It was found that for 50% of all prefixes in the test partition of the total datset, the absolute prediction error was less than or equal to 3.673 days. This was confirmed to be sufficient by the supply chain manager of Company X.

- *Deployment*
  This CNN was subsequently deployed in the machine learning workbench of Company X by writing a Python script transforming the input data for new cases into the right format and predicting the number of days between contractual delivery date and actual delivery date for the purchased items with the trained CNN. The result is shown in Figure 3.

Drilldown by Purchasing Document

PO Num	Item	contractual delivery date	prediction	predicted delivery date
5506355611	00001	Fri Oct 21 2022 00:00:00	1.0037072896...	Sat Oct 22 2022 00:00:00
5506355612	00001	Tue Oct 18 2022 00:00:00	1.3599542379...	Wed Oct 19 2022 00:00:00
5506355614	00001	Tue Oct 18 2022 00:00:00	3.2748460769...	Fri Oct 21 2022 00:00:00
5506355617	00001	Tue Oct 18 2022 00:00:00	-2.1557650566...	Sun Oct 16 2022 00:00:00

Figure 3: The predicted delivery dates for purchased items within the Celonis

After the predictions for the delivery date could be generated with the CNN, the prescriptive process monitoring part was continued. This phase resulted in the deployment of a prescriptive model that recommends which purchased items from suppliers need to be prioritized for expediting for the day, taking into account the predicted delivery date for purchased items. In the following, the most important steps that had to be performed are explained, again based upon the BPMP-PM methodology.

- *Method Selection & Implementation*
  The newly developed prescriptive model was based upon the existing expedite framework of Company X which consists of an expedite dashboard, showing the prescriptive input data as well as generated priorities for the purchased items, and weighed scoring model to calculate an expediting priority score. Several changes were made to the framework, which finally resulted in the newly developed prescriptive model. First of all, the range of items being expedited was increased by adding an extra filter to the dashboard such that not only the already overdue items can be selected, but also the items that will become overdue within two weeks and are predicted to be delivered more than 1 day late. Subsequently, for all these items a new expedite score is calculated where the factor ‘days overdue’ was changed such that it took the predicted delivery date into account as produced by the CNN. This resulted in new values for the expedite score for the purchased items which leads to a new and different priority list for expediting.

- *Deployment*
  The prescriptive model was evaluated by means of a past and future analysis. However, the future analysis required the model to be deployed. Therefore, this step is ex- plained before the evaluation step. The prescriptive model was deployed within the Celonis environment of Company X. Since the

predictive model was deployed within Celonis as well, the values for the predicted delivery date for items could be retrieved within the existing expedite dashboard. Next, the filter 'orderline overdue' was changed in the expedite dash- board to be able to add the not yet overdue items to the expedite priority list. Moreover, a new formula for the expedite score was added within the expedite dashboard including the updated computation for factor 'days overdue'. An example of the newly generated priority list for expediting after deploying the prescriptive model is shown in Figure 4. It can be noticed that one of the most urgent items for expediting is now a purchased item that is not yet overdue but predicted to be delivered very late.

Client	Purchasing Document	Item	Planned delivery date	Predicted delivery date	Predicted days overdue	New Expedite Score	Original Expedite Score
411	5506262171	00001	2022-08-08	2022-07-25	-14	10	10
411	5506303998	00001	2022-10-12	2022-09-13	-29	10	10
411	5506307869	00001	2022-09-20	2022-09-29	9	10	10
411	5506323040	00001	2022-10-05	2022-09-26	-9	10	10
300	4502278952	00020	2022-09-02	2022-08-15	-18	10	10
300	4502278952	00030	2022-09-02	2022-08-20	-13	10	10
300	4502286017	00010	2022-10-28	2022-11-16	19	9.8	8.6
300	4502308401	00010	2022-10-17	2022-10-17	0	9.8	9.8
300	4502308402	00010	2022-10-17	2022-10-17	0	9.8	9.8
300	4502308403	00010	2022-10-17	2022-10-20	3	9.8	9.8

Figure 4: Expediting priority list based on new expedite score

- *Evaluation*

  The performance of the prescriptive model was evaluated by means of a historical and future analysis. The past analysis showed that for around 77% of the past expedited items it could have been predicted ahead of time that the items would arrive late. If the new prescriptive model was implemented at that time, these items could have been expedited before they would already be overdue. Furthermore, the future analysis showed that around 10% of the not yet delivered most critical purchased items would become overdue soon and were predicted to be delivered late. With implementing the new prescriptive model, these items are added to the expedite priority list, as well as assigned a higher priority for expediting in case the predicted delivery date is later than the planned delivery date. This could prevent late deliveries from happening or from being very extreme by contacting suppliers earlier. This reduces risk since those items are very critical to be able to perform the maintenance activities and are of high order value. A critical note to the prescriptive model is that it does not take into account the accuracy of the CNN. Therefore, items could be incorrectly included into the expediting priority list as they were incorrectly predicted to be delivered too late. Moreover, it affects the reliability of the new expedite score and can lead to a bias within the generate expediting priority list. Therefore, it is recommended to monitor the effect of the prediction error on the expedite score while validating the deployed model, to get an understanding of whether items are wrongly prioritized. This could for example indicate whether the new expedite score needs to be change.

  To summarize, the results show that by implementing the CNN as well as the new prescriptive model using the generated predictions by the CNN, Company X is enabled to act proactively and intervene before items are delivered late. The CNN creates insight into which items are expected to be delivered late. Hence, by using the new prescriptive model these items can be included within the priority list for expediting and a higher priority can be assigned to items which are predicted to arrive later than the planned delivery date. Therefore, Company X can call suppliers before the items are actually overdue. Moreover, by giving more priority to items for expediting which are not overdue yet but are predicted to arrive very late, impact can be made on the OTIF rate since those items can be prevented from actually arriving late or from arriving extremely late.

Scenarios analysis for disruption recovery

This research has been conducted at Hilti and involved two main phases. First, we developed a tool to increase transparency on the material availability, which is crucial information for the S&OP process. Then, we developed a decision support tool leveraging an optimization model to support capacity planners in exploring different scenarios corresponding to different disruptions and determining the best mitigation strategy according to the KPI(s) of interest. Results of both phases are summarized below.

A framework to enhance transparency in material availability

S&OP aims to close the gap between customer demand and available plant capacities. The expected demand is based on the global forecast and is expressed in pieces and hours. The capacity is measured on three levels: machinery, man power and materials. Machinery and man power are measured in hours and can be compared to the demand. When the project started, there was no measurement for the material availability at Hilti that could be compared to the demand. The reason for this is that no inventory of the materials is held at the moment of the S&OP meetings. Production only starts in the same month as the demand should be satisfied, while the S&OP meetings take place before the discussed month starts. Possible shortages in materials are found during the same month as the demand should be satisfied. In the current situation, it happens that man power and machinery cannot work as planned because there is a sudden shortage in materials. This leads to redundancy and inefficiency of the process.

Each material that is produced consists of multiple components. If these components are available at the start of the month, the materials can be produced in that month as well. To find the expected material availability, the availability of the components should be found first. The component availability can be determined based on the current and in-transit inventories. However, it is computationally expensive to do these calculations for each component and material individually. Therefore, the goal of the project was to create a tool that defines the material availability. A dashboard has been designed to combine the demand data with the data on component availability to identify possible shortages before the month starts, thus providing valuable input for the S&OP decision making.

The component availabilities are found by combining data from multiple sources and formats. These are combined into one structure that is the input for the dashboard. The core of the structure is the Bill of Materials which includes the materials and their components. The demand for each material is based on the global forecast. The capacity is determined for each component and is based on the inventory. The inventory depends on orders placed at the suppliers. These can be external suppliers or other Hilti plants. To be able to compare the demand to the capacities, the demand is translated to component level as well. The dashboard translates the information of these different elements into a format that can be using during S&OP. Figure 5 shows the table of component availability generated for a set of selected components.

KPILight	Production Line	Component number	Component description	Total requirements (PC)	Tool numbers	Tool names	Tool shortage (incl. transit) (PC)	Tool shortage (excl. transit) (PC)	Coverage by current stock (%)	Vendor	Lead time (days)	PA (score)	Special procurement
●	Z2	AT4739	*	298	TOOL A, TOOL B	*	182	182	38.9	SUPPLIER A	10.0	0.09	A
●	Z2	GF2739	*	2686	TOOL A, TOOL B , TOOL C, TOOL D, TOOL E, TOOL F, TOOL G, TOOL H, TOOL I, TOOL J,	*	1010	1330	50.5	SUPPLIER B	10.0	0.69	A
●	Z2	ER2937	*	3511	TOOL A, TOOL B	*	0	0	141.1	SUPPLIER C	25.0	No info available	A

Figure 5: Table of the component availability dashboard

It has been validated through a case study at two production lines at Hilti. The visuals are dis- played below, where the left chart represents Z1 and the right chart represents Z2. It can be seen that the red components account for 31.8% to 22.1% of the total amount of components in scope. This means that for these components a shortage in components is expected, which indicates a shortage in the materials it is used for as well. During the case study, each red component is evaluated and extra orders are placed when needed.

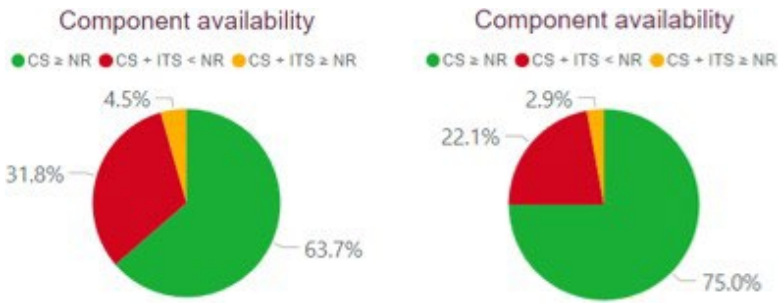


Figure 5: Visual component availability for plant Z1 and Z2

In addition to the case study, a scalability test has been carried out. For this test, the dashboard is created for eight additional production lines in Plant XZ. This test confirmed that the dashboard is scalable and finds results for production lines that were initially not in scope. The main finding of the scalability test is that there can be made a distinction between production lines with high inventories and high certainty and production lines with lower inventory levels and lower certainty.

Scenarios analysis for S&Op supported by an optimization model

The sales and operations planning (S&OP) process is an important process in any manufacturing environment. This process, which is on a tactical level, is typified by balancing the expected demand with the resources required for production for a specific time horizon. Whereas previously the S&OP process was conducted in isolation, a shift has been made to a more collaborative approach between departments. In doing so, the decision-making process is more streamlined which should in practice yield more cost-effective decisions. However, the S&OP process remains complicated as the departments have competing interests. Additionally, due to the many interdependencies between resources and production, it is difficult for the decision-maker to find an optimal production plan within the considered time horizon. This is further exacerbated by the inherent uncertainty within this process. This research developed a decision-support tool which helps alleviate the previously mentioned issues by providing the end-user the ability to create and assess different scenarios. For this project, the methodology is based on the problem-solving cycle as defined by Van Aken, Berends, and Van der. In the first step of the cycle the problem was defined and scoped. These have been derived from the initial project description and further refined by meetings with the company representatives.

Summing up, there is a lack of quantitative support when making capacity related decisions for the CP which ultimately leads to inefficient and sub-optimal decision-making. The second step was to analyse the problem and gather information about the root cause of the problem. This was done by arranging one-on-one meetings with the stakeholders involved. Furthermore, S&OP meetings were attended to observe the problem from an outside perspective. Additional infor- mation was gathered from previous projects and presentations which provides an objective overview of Hilti's S&OP process. The analysis revealed that the problem as defined previously is representative of the problem as experienced in practice. The main issues causing the problem are

1) lack of time due to short-decision time-frame,
2) difficulty obtaining required data and
3) high complexity in decision-making.

In the third step, a fitting solution design will be developed that fits the current context. To gain inspiration for the solution design, an extensive literature review will be conducted. In the environment of capacity planning, uncertainty plays a key role which is reflected in the literature. Generally, there can be two types of model which fit the context namely stochastic and deterministic models. Due to the context, stochastic models which inherently includes uncertainty are deemed unsuitable due to the unavailability of historic data. Additionally, the model should be able to provide a unique optimal solution for each scenario under consideration and therefore a deterministic model is selected.

To ensure that uncertainty is still included in this model, the deterministic model will be adjusted accordingly in the form of allowing the end-user to manually adjust the parameter values. In this process, it is also important to regularly schedule meetings with the stakeholders. The main purpose of these meetings was to keep the stakeholders apprised of the model's development and also gather context-specific constraints and demands. Additionally, it is important to determine whether the stakeholders prefer practicality or accuracy as this shapes the direction of the model development. A depiction of the developed conceptual model can be found in Figure 6.

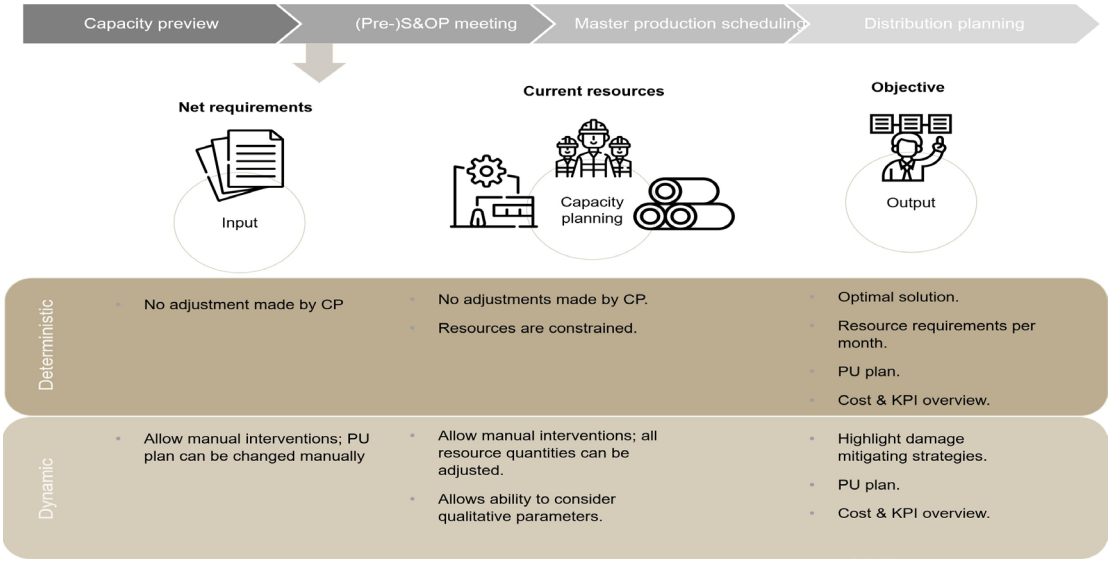


Figure 6: The conceptual model

The dynamic model leaves room for the CP to alter the resources in future periods to create scenarios whilst the deterministic model determines the optimal quantity of resources given an objective. A common way to obtain an optimal solution to these types of problems is by means of linear programming. We hence developed a mathematical model suitable for a MILP solver. We held discussions with the stakeholders and with the company experts to determine suitable cost function, decision variables, parameters and constraints.

After an initial model is developed, an appropriate environment should be selected for integration. This environment should both be 1) able to execute the model and 2) be user-friendly. Based on these requirements, it was decided to implement and execute the model in Python. However, the actual user interface has been developed in Excel, to make its adoption easier for the involved stakeholders. Figure 7 provides an excerpt of the developed dashboard.

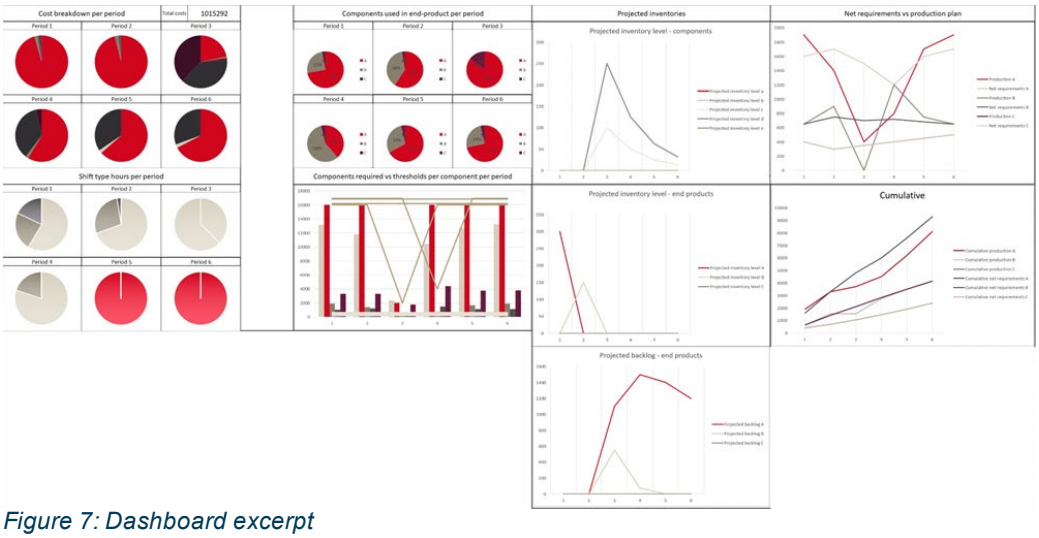


Figure 7: Dashboard excerpt

After the model's output has been verified and validated, the model has been tested by the CPs. To this end, we developed three case studies selecting three of the most common S&Op issues. The first scenario includes an acute component shortage. The second scenario evaluates a significant reduction in labour hours available. The third scenario investigates the impact of ordering a component which is uncertain to arrive with a short lead time. To test these case studies (scenarios), a hypothetical production line is created. This production line uses parameter values which are in close resemblance to several of Hilti's production lines. As an example, Figure 8 shows the model output for the first scenario.

Total costs = 916053,80 CHF	**Periods**				
Costs (in CHF)	*1*	*2*	*3*	*4*	*5*
Total purchasing costs	53280	153448	148970	109252	121650
Total day shift costs	856	4800	4800	3201	3755
Total night shift costs	0	33,60	372	0	0
Total idle costs	2144	0	0	0	0
Total component inventory costs	655,20	237	0	0	0
Cost of lost sales "A"	80000	57200	2700	0	0
Cost of lost sales "B"	39400	0	0	0	0
Total costs	176335,20	215718,60	156842	112453	125405
Decision variables					
Production "A"	0	2156	2590	1254	1600
Production "B"	256	1144	700	720	680
Production "C"	400	300	350	400	450
Component "a" required	1680	16800	16800	10270	11850
Component "b" required	12730	16000	16000	13470	14800
Component "c" required	500	1656	2590	1254	1600
Component "d" required	656	1444	1050	1120	1130
Component "e" required	2512	3788	3150	3440	3610
Day shift hours required	57,07	320	320	213,4	250,33
Night shift hours required	0	1,87	20,67	0	0
Idle time	142,93	0	0	0	0
Inventory "b"	10170	3950	0	0	0
Inventory "c"	500	0	0	0	0
Backlog "A"	1600	1144	54	0	0
Backlog "B"	394	0	0	0	0

Figure 8: Model output for scenario 1

Additionally, the model has been tested for its scalability and an implementation plan will has been provided for the company such that the actual intervention itself, which is performed by the company, can be adequately executed.

FIRM NETWORK LEVEL

This project empirically investigated disruptions of supply chains, and consisted of two empirically grounded research papers. The first research paper examined how disruptions propagated through the complex network of the Boeing-Airbus duopoly, by relying on Boeing 737 MAX crashes and subsequent operational glitches. The second research paper illustrated how U.S. tariffs during 2018-2019 impacted global supply chains. Both research papers have important implications for supply chain disruption management and resilience.

The main findings of the first research paper are summarized as follows. First, we built our complex network of Boeing and Airbus upon the FactSet Supply Chain Relationship database. This network included tier-1 suppliers, customers of tier-1 suppliers, tier-2 suppliers, and customers of tier-2 suppliers of both focal firms, i.e., Boeing and Airbus. Moreover, this network displayed complex and interconnected network structure. Relying on event study methodology to examine how four sequential disruptive events impacted this supply network, we found differential impacts of these four disruptions. Specifically, for event 1 (i.e., Lion Air crash at October 29, 2018), we could not find any significant impact because this event was generally regarded as an accident. However, we found significant spillover effects for event 2 (i.e., Ethiopian Air crash, March 10, 2019). This event had a negative effect on Boeing's tier-1 suppliers, customers of tier-1 suppliers, tier-2 suppliers, and customers of tier-2 suppliers. This disruptive impact also propagated through Airbus' tier-1 suppliers, customers of tier-1 suppliers, tier-2 suppliers and customers of tier-2 suppliers. We further found a propagation asymmetry between Boeing's suppliers and customers for this event. In contrast, we could not find any significant effect for event 3 (i.e., announcement of production cut, April 4, 2019). Finally, for event 4 (i.e., December 16, 2019), we found overall negative effects that were less severe compared to the effects of event 2.

The main findings of the second research paper are summarized as follows. We extracted 222 importing manufacturers from the FactSet Shipping database, and for each manufacturer, we focused on monthly amounts of sourcing from January 2014 to December 2020 (to distinguish between the potential effects from Covid-19 pandemic). Therefore, we had 222 unique time series for each importer. Due to high-dimensionality of time series, we adopted an unsupervised machine learning approach, i.e., multivariate time series clustering and identified seven unique clusters (i.e., groups) for these manufacturers. By utilizing the so-called intervention analysis in time series, we found that while some firms had a disruptive effects in their global sourcing, other firms mitigated this by potentially using strategies such as dual or multiple sourcing. We used the same intervention analysis with a focus on firms sourcing from China and confirmed similar patterns.

Methodology

We adopted different methodologies to assess disruptive effects for these two different research papers.

- *Research Paper 1*
  For the first paper, we established our complex supply network from the FactSet Supply Chain Relationship database. FactSet is a financial information and technology provider, and this database collects the data from multiple sources, including operations segments reported in SEC fillings required by Regulation SFAS No. 131 which mandates that all U.S. public firms disclose their customers comprising more than 10 of their annual revenue, as well as other public filings, company websites, news reports, and other proprietary research. Therefore, this database has an advantage over other commonly used sources such as the Compustat segments. This database has been used to investigate bullwhip effect and financial risks propagating through supply chains. To explore the spillover effects within the complex supply networks within this duopoly, we further selected tier-1 and tier-2 suppliers of Boeing and Airbus, and customers of tier-1 suppliers' and tier-2 suppliers'. We also included Boeing's customers to investigate asymmetric spillover effect between Boeing's suppliers and customers.

  Based on this complex supply network, we utilized event study methodology to assess how stock market reacted to the four aforementioned disruptive events. Ideally we would like to use operational indicators (such as inventory or working capital) to measure the impact of the 737MAX crashes on the

supply chain, but these are difficult to observe at the required granularity. It is difficult to ascribe a portion of such operational metrics (say inventory, or accounts receivable) in their contribution to the supply chain in consideration without detailed product-level data. Hence, we measured the impact of the disruptions on the operations using stock market reactions as a proxy. This approach combines the network analysis of supply chains with the short term event study methodology. Specifically for event study methodology, this methodology is used to estimate abnormal returns associated with specific events after controlling for market-wide factors that can potentially influence stock prices. An event study quantifies the gain or loss in value of a firm, or a group of firms, by measuring the stock market's reaction to a particular event. By examining the market reactions following the events, we ascribe causality to the way in which these impact the firms' value. Specifically, an event's impact on a firm is measured through its abnormal returns, cumulated over a certain time-window following the event in question. Abnormal returns measure the difference between the observed evolution of a firm's valuation and a counterfactual based on the estimated valuation had the event not occurred.

- *Research Paper 2*

  For the second research paper, we extracted monthly time series data based on the FactSet Shipping database, the same data provider as the first research paper. This database covers transactions to 320 U.S. ports from nearly 1,400 non-U.S. ports from November 2013, and is updated continuously. This database includes transactional details such as cargo content descriptions, departure and arrival ports, and shipper/consignee relationships, associated with maritime freight traffic subject to tracking or taxation by the U.S. Customers and Border Patrol. The dataset is sourced from bills of lading, and includes important product information, such as HTS codes. Because most of tariffs imposed were intermediate inputs which would be used for production, we were specifically interested in importing manufacturers. By linking consignee unique identifiers based on monthly imports to SIC manufacturing 4-digit codes (2000-3999), we identified 4,262 unique manufacturers. Suitable for time series analysis of monthly imports, we required that manufacturers have equally-spaced monthly imports covering January 2014 to December 2019 to distinguish the effects of Covid-19 pandemic. Finally, we obtained 222 unique manufacturers for our further analyses.

  We utilized two methods to address our research questions. First, due to high-dimensionality of time series, we used an unsupervised machine learning approach, i.e., multivariate time series clustering to identify structures of these manufacturers. Clustering analysis is a task which is used to create groups of objects, based on the (dis)similarity of objects. Each group is called a cluster, and the clustering algorithms to perform this task typically vary according to specific research purposes. According to the nature of data, clustering algorithms can be applied to both static data and dynamic data, such as time series in our case. Here we focused on time series clustering. The most important elements for this clustering task include distance measure, the prototype extraction function, the clustering algorithm itself, and clustering evaluation, i.e., Cluster Validity Indices (CVIs). We utilized R package dtwclust for our analyses.

  After clustering procedure, we then relied on intervention analysis to analyze the disruptive effects for each cluster we identified. Intervention analysis is concerned with how an event, such as policy changes, impacts the behavior of one time series, and is considered as one special type of transfer function analysis. Therefore, intervention analysis provides us an appropriate way to assess how the U.S. tariffs during 2018-2019 influence firms' sourcing behaviors. In the intervention analysis, we need to assume that an intervention event has occurred at a known point in time of a time series. Here we identified March 2018 as the main month of intervention because the large-scale U.S. tariffs were effective initially in March 2018. Due to the fact that firms may respond even before this time period, we conducted post-hoc analysis taking into other possibilities of intervention time.

Detailed findings

- *Research paper 1*
  We first focused on the results for the first research paper. Different from prior research, we study a "disruptive event" that can better be defined as a sequence of events, each with unique features. We resketched the timeline for each event as follows: (1) The Lion Air crash in October 2018, (2) the Ethiopian Air crash in March 2019, (3) Boeing's production cuts announced in April 2019, and (4) Boeing's production halt announced in December 2019. These have a number of unique characteristics.

  First, we distinguished between Supply Chain disruptions and related trigger events. Formally, only events 3 and 4 – the production cut and the production stop – can be classified as a material supply chain disruption. Specifically, event 3 was a partial disruption and event 4 was a total disruption. Events 1 and 2 constituted what we defined as trigger events; events that in hindsight can be rationalized as clearly building up to the ultimate disruption but which, at the time, could only be partially understood.

  Looking back, events 1 and 2 were technically identical but differed in their context. Both were fatal crashes with a comparable number of victims, widely held to have been caused by a combination of questionable design of the aircraft's MCAS system and improper training and maintenance procedures. The major difference between the events was not technical but one of public perception; whereas investigations of the first crash followed established procedures and the Indonesian government cleared the 737MAX to fly 3 days after the accident, the second crash was immediately identified as a signal of likely design or systematic maintenance issues with the new MAX series of planes. A second crash within 5 months had few and notorious antecedents – articles quickly appeared likening the 737MAX and the De Havilland Comet, one of the most infamous examples of design failure in aviation history, with three fatal crashes within 12 months in the early 50's.

  Even though event 2 eventually triggered a downstream disruption in the operation of the Boeing fleets (e.g., the FAA grounded all 737MAX aircraft 2 days after the event, on March 13th), neither of these events generated a material disruption in the manufacturing supply chain. Thus, we argued that any differences in the market reaction immediately following these events can be attributed to the signals they sent about the underlying operations of Boeing. Previous studies contended that not all SC disruptions were evaluated equally by the market. In particular, the market did not place the blame of an external disruption (e.g., a natural disaster) on the companies affected. In contrast, an internal disruption (caused by, e.g., quality control issues) was often interpreted as a signal of deeper operational issues and penalized accordingly. Following this line of reasoning, SC disruptions destroy shareholder value not (entirely) because of the loss of material value, but because they signal operational mismanagement.

  Based on this, we maintained that – in the absence of full information – the market broadly viewed event 1 as an external event and therefore did not immediately ascribe operational mismanagement to Boeing; we did not expect this accident to derive in significant financial consequences on the aircraft manufacturing supply chain. In contrast, the occurrence of event 2 in such short order was immediately regarded, by the market and public opinion, as a signal of operational manufacturing issues and thus expected to negatively impact the shareholder's value of Boeing's supply chain. Therefore, we proposed the following hypotheses.

  Hypothesis 1: The Lion Air crash would not have significant financial impact on the supply chain of the Boeing-Airbus duopoly.

  Hypothesis 2: The Ethiopian Air crash would have significant financial impact on the supply chain of the Boeing-Airbus duopoly.

  Events 3 and 4 were qualitatively similar. They both comprised of a (planned) SC disruption propagating upstream and downstream from Boeing; they both affected the same product, and thus the same potential set of partner firms. They differed in the extent of the disruption: Immediately after

the news about the second crash and the faulty MCAS, Boeing decided to cut its 737MAX production by 20% (event 3), and towards the end of 2019, facing significant challenges in its re-certification efforts, the company made the decision to completely halt production (event 4).

Devoid of context, the effect of these disruptions should be proportional to their material impact; a partial disruption leading to a smaller financial impact than a full disruption. Naturally, these events were not devoid of context. To the extent that event 2 signaled operational issues, an argument can be made that these were already priced-in and therefore no new (damaging) information was added by event 3. Civil aviation authorities around the world, for example, had already grounded the 737MAX fleets, and it was clear that this would continue throughout 2019. Moreover, from a purely operational perspective, Boeing took immediate measures to try and minimize the material impact on its key suppliers.

Prior research shows that when an event is anticipated the economic impact of the announcement itself is only attributable to the resolution of the uncertainty of the event itself — the larger the uncertainty, the larger the impact of the announcement. In the case of event 3, we anticipated that investors had already developed expectations regarding the potential production cut of the 737MAX by Boeing. Furthermore, considering the close proximity of this event, it was likely that the market had already factored in this likelihood and accounted for the uncertainties associated with future 737MAX production.

We followed a similar line of reasoning in anticipating the impact of event 4. There were two main dynamics driving its impact: on the one hand, the material SC disruption associated with event 4 (full production halt) was much larger than that of event 3 (20% reduction), on the other hand, there had been a general awareness for several months that Boeing may need to make this decision — thus investors and supply chain partners could have anticipated the occurrence of the event.

Although the announcement of the production stoppage triggered a much larger material SC disruption than event 3, its impact would also be anticipated by analysts and supply chain partners to a certain extent. Following the occurrence of event 3, adjustments to the 737MAX production schedule, material flows, and associated transportation became necessary. In response, tier-1 suppliers would further modify their own production schedules to ensure the smooth functioning of the supply chain for both suppliers and customers. Additionally, from an investor's perspective, there had been a general awareness for several months that Boeing would need to make this decision. As a result, the market had already adjusted its pricing to account for the anticipated production stoppage. We proposed the following hypotheses:

Hypothesis 3: The production cut would have significant financial impact on the firms in the Boeing-Airbus duopoly, but will not be as severe as that from the second crash.

Hypothesis 4: The production stop would have significant financial impact on the firms in the Boeing-Airbus duopoly, but will not be as severe as that from the second crash.

We investigated the asymmetry between upstream suppliers and downstream customers, considering not only the magnitude of the financial impact but also its temporal nature. When the external environment impacts a focal node in the supply network, its effects are bound to propagate both upstream and downstream. Under a make-to-order system, the key Original Equipment Manufacturers (OEMs) must work closely with customers because customers may provide key design features for the products they would like to have. Therefore, when Boeing's 737MAX encountered design and production problems, Boeing needed to pay more attention to negotiating with customers. This disproportionate attention may cause an asymmetry in the propagation of the impact through the supply chain network. Moreover, investors may expect that downstream customers typically have different products to choose from other manufacturers (competitors), but upstream suppliers will lose production orders when demand for a product goes down or it is discontinued. As a result, the impact of the 737MAX disruption was likely to be more persistent and long-lasting upstream compared to downstream. While downstream customers may adjust their business by seeking alternative products or services for their continued survival, the cancellation of production means that suppliers no longer

have customers, leading to a longer-term impact on their financial performance. Based on these considerations, we formulated the following hypothesis:

Hypothesis 5: The financial impact of the 737MAX disruption was expected to exhibit an upstream/downstream asymmetry, with the impact persisting for a longer duration upstream compared to downstream.

Empirical findings from our event study generally confirmed these hypotheses. We could not find any significant effect for event 1. In contrast, we found significant spillover effects across the supply network of the Boeing-Airbus duopoly for event 2.
Table 3 shows the results of event 2 for Boeing's supply chains while Table 2 showed the results of event 2 for Airbus' supply chains. Focusing on the main event time window of Days (0, 10), for Boeing's tier-1 suppliers, both the mean and median CARs were -2.16% and -2.90% with $p < 0.05$ and $p < 0.01$, respectively. Among these firms, 79.35% experienced a negative stock market reaction.
A similar pattern was observed for customers of Boeing's tier-1 suppliers, with mean and median CARs of -2.10% and -2.25%, both significant at $p < 0.01$. Among them, 68.39% of these firms showed a negative stock market reaction. For tier-2 suppliers, the mean and median CARs were -2.18% and -2.15%, both significant at $p < 0.01$, with 70.08% of these firms experiencing a negative stock market reaction.

Likewise, customers of Boeing's tier-2 suppliers had mean and median CARs of -1.68% and -1.73%, both significant at $p < 0.01$, with 63.49% of these firms suffering a negative stock market reaction. These results strongly supported Hypothesis 2, indicating that the potential disruption originating from Boeing propagates throughout the entire supply networks of Boeing.

*Table 3: Impact of the Second Crash on Boeing's US Supply Chain. Note: *p<0.10,**p<0.05,***p<0.01*

Tier-1 Suppliers								Customers of Tier-1 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[0, 3]	92	-1.12	-2.08***	-1.59	-4.87***	77.17	-5.20***	[0, 3]	367	-1.18	-4.74***	-1.11	-8.48***	67.85	-7.16***
[0, 10]	92	-2.16	-2.43***	-2.90	-4.72***	79.35	-5.62***	[0, 10]	367	-2.10	-5.09***	-2.25	-8.26***	68.39	-7.37***
[0, 15]	92	-1.72	-1.61	-2.33	-3.54***	72.83	-4.37***	[0, 15]	367	-1.39	-2.80***	-0.94	-4.21***	57.77	-3.30***
Tier-2 Suppliers								Customers of Tier-2 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[0, 3]	391	-1.32	-4.62***	-1.15	-7.85***	67.52	-6.90***	[0, 3]	860	-0.63	-2.84***	-0.89	-7.38***	61.98	-7.26***
[0, 10]	391	-2.18	-4.62***	-2.15	-8.22***	70.08	-7.92***	[0, 10]	860	-1.68	-4.62***	-1.73	-8.98***	63.49	-8.14***
[0, 15]	391	-1.76	-3.08***	-1.32	-4.90***	60.10	-3.97***	[0, 15]	860	-1.57	-3.57***	-1.13	-6.21***	57.21	-4.46***

Table 4 presents the results for Airbus' supply chain under Event 2. Overall, all results from every event window and every layer of Airbus' supply chain exhibited negative and significant effects, providing strong support for Hypothesis 2. Specifically, focusing on the Days (0, 10) as the main time window, for Airbus' tier-1 suppliers, mean and median CARs of -3.09% and -2.72% were observed, both significant at $p < 0.01$. Among these firms, 84.38% displayed negative reactions in the stock market. As for customers of Airbus' tier-1 suppliers, mean and median CARs of -1.87% and -2.09% were recorded, both significant at $p < 0.01$. Among them, 66.12% exhibited negative reactions in the stock market. Furthermore, for Airbus' tier-2 suppliers, mean and median CARs of -2.20% and -2.35% were observed, both significant at $p < 0.01$. Among these firms, 69.72% show negative reactions in the stock market. Finally, for customers of Airbus' tier-2 suppliers, mean and median CARs of -1.27% and -1.58% were recorded, both significant at $p < 0.01$.
Among them, 62.11% react negatively in the stock market. In summary, the results presented in Tables 1 and 2 provided strong support for Hypothesis 2.

*Table 4: Impact of the Second Crash on Airbus' US Supply Chain. Note: *p<0.10,**p<0.05,***p<0.01*

Tier-1 Suppliers								Customers of Tier-1 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[0, 3]	64	-1.79	-3.26***	-1.69	-4.98***	84.38	-5.48***	[0, 3]	425	-0.95	-3.75***	-1.02	-7.34***	65.65	-6.77***
[0, 10]	64	-3.09	-3.40***	-2.72	-4.71***	84.38	-5.48***	[0, 10]	425	-1.87	-4.46***	-2.09	-7.26***	66.12	-6.96***
[0, 15]	64	-2.09	-1.90*	-2.29	-2.34***	68.75	-2.98***	[0, 15]	425	-1.38	-2.73***	-0.94	-3.92***	57.18	-3.27***
Tier-2 Suppliers								Customers of Tier-2 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[0, 3]	393	-1.14	-4.06***	-1.13	-7.47***	68.19	-7.19***	[0, 3]	921	-0.39	-1.72*	-0.82	-6.28***	61.24	-6.99***
[0, 10]	393	-2.20	-4.75***	-2.35	-8.36***	69.72	-7.80***	[0, 10]	921	-1.27	-3.42***	-1.58	-8.40***	62.11	-7.52***
[0, 15]	393	-1.92	-3.42***	-1.46	-5.29***	60.31	-4.06***	[0, 15]	921	-0.97	-2.14**	-1.01	-5.66***	56.46	-4.09***

We found no significant effect for event 3, confirming our expectation that this event had been expected by investors and therefore stock market reacted not strongly for this event. In contrast, we found some significant negative spillover effect for event 4, but the effect was not as negative as the effect of event 2. These findings generally support our hypothesis 4. Table 5 summarizes the results for Boeing's supply chain during this event. Using the event window (-1, 10), we found that the mean CAR for Boeing's tier-1 suppliers was -0.72%, not statistically significant. However, the median CAR for these firms was -2.00%, significant at the 0.01 level. About 68.48% of these firms experienced a negative stock market reaction. Similarly, for customers of Boeing's tier-1 suppliers, the mean CAR was -0.69% (non-significant), while the median CAR was -1.32%, significant at the 0.01 level. Around 65.48% of these firms reacted negatively. Moving to Boeing's tier-2 suppliers, the mean CAR was -0.14% (non-significant), but the median CAR was -1.01%, significant at the 0.01 level. Approximately 61.18% of these firms reacted negatively. Finally, for customers of Boeing's tier-2 suppliers, the mean CAR was non-significant, but the median CAR was -0.90% (significant at the 0.01 level). Around 58.95% of these firms experienced negative reactions. Overall, our results supported the idea that firms at various levels of Boeing's supply chain had negative reactions, particularly evident in the medians. However, these CARs were smaller in magnitude compared to those observed in Event 2 (the trigger event).

*Table 5: Impact of Production stop on Boeing' US Supply Chain. Note: *p<0.10,**p<0.05,***p<0.01*

Tier-1 Suppliers								Customers of Tier-1 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[-1, 3]	92	-0.83	-1.39	-1.28	-2.95***	68.48	-3.52***	[-1, 3]	365	-0.54	-1.99**	-0.80	-4.75***	62.47	-5.07***
[-1, 10]	92	-0.72	-0.77	-2.00	-3.17***	68.48	-3.52***	[-1, 10]	365	-0.69	-1.64	-1.32	-5.02***	65.48	-6.22***
[-1, 15]	92	0.36	0.32	-2.02	-2.57***	59.78	-1.85*	[-1, 15]	365	-0.80	-1.60	-1.66	-6.38***	64.66	-5.90***
Tier-2 Suppliers								Customers of Tier-2 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[-1, 3]	389	-0.41	-1.28	-0.72	-3.59***	57.33	-2.89***	[-1, 3]	855	-0.32	-1.33	-0.60	-4.64***	57.89	-4.86***
[-1, 10]	389	-0.14	-0.29	-1.01	-4.38***	61.18	-4.41***	[-1, 10]	855	0.27	0.70	-0.90	-4.10***	58.95	-5.48***
[-1, 15]	389	0.18	0.30	-1.24	-4.54***	58.61	-3.40***	[-1, 15]	855	0.30	0.66	-1.56	-6.46***	59.53	-5.82***

Table 6 presents the main results for Airbus' supply chain in response to Boeing announcing a stop in 737MAX production. We also considered the event window (-1, 10) for analysis. For Airbus' tier-1 suppliers, the mean and median CARs were -1.65% and -2.73% (with $p < 0.10$ and $p < 0.01$, respectively). Around 84.38% of these firms had negative reactions in the stock market. Customers of Airbus' tier-1 suppliers exhibited a non-significant mean CAR of -0.47%, but a significant median CAR of -1.33% ($p < 0.01$). Roughly 64.45% of these firms experienced negative reactions. Regarding Airbus' tier-2 suppliers, the mean CAR was 0.16%, while the median CAR was -0.92% ($p < 0.01$). Around 60% of these firms had negative reactions. Finally, for customers of Airbus' tier-2 suppliers, we observed a positive and significant mean CAR of 0.74% ($p < 0.10$). However, the median CAR was -0.81%, significant at the 0.01 level. About 57.38% of these firms experienced negative reactions. Similar to Boeing's supply chain, we found that the magnitude of CARs is lower compared to those observed in Event 2. Hence, our results provided support for Hypothesis 4.

*Table 6: Impact of Production stop on Airbus's US Supply Chain. Note: *p<0.10,**p<0.05,***p<0.01*

Tier-1 Suppliers								Customers of Tier-1 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[-1, 3]	64	-1.32	-2.16**	-1.69	-4.43***	84.38	-5.47***	[-1, 3]	422	-0.43	-1.55	-0.78	-4.40***	61.85	-5.16***
[-1, 10]	64	-1.65	-1.74*	-2.73	-5.09***	84.38	-5.47***	[-1, 10]	422	-0.47	-1.10	-1.13	-4.61***	64.45	-6.23***
[-1, 15]	64	-0.95	-0.84	-2.98	-4.68***	75.00	-3.97***	[-1, 15]	422	-0.68	-1.33	-1.64	-6.40***	63.27	-5.74***
Tier-2 Suppliers								Customers of Tier-2 Suppliers							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[-1, 3]	390	-0.18	-0.57	-0.69	-2.69***	57.69	-3.04***	[-1, 3]	915	-0.11	-0.43	-0.58	-4.24***	57.05	-4.45***
[-1, 10]	390	0.16	0.33	-0.92	-3.64***	60.00	-3.95***	[-1, 10]	915	0.74	1.90*	-0.81	-3.65***	57.38	-4.65***

Finally, Table 7 summarized the main results for Boeing's U.S. customers during the four events. Surprisingly, for event 1, Boeing's customers experienced positive CARs (both mean and median) within the event windows of (0, 3) and (0, 10). This suggested that the accident did not significantly impact Boeing's U.S. customers. The major negative reaction was observed in event 2, aligning with the response of Boeing's suppliers. However, we found that the mean and median CARs for Boeing's customers are -4.44% ($p < 0.05$) and -4.55% ($p < 0.01$) respectively. Around 81.25% of these customers had negative reactions in the stock market. Comparing these results with those presented in Table 1, we observed an asymmetry, with customers being more affected than tier-1 suppliers and other parts of Boeing's supply chain. Immediately following Events 3 and 4 (the announcement of production cut and production stop), we saw no significant negative market reactions for the customers. By late December 2019 fears of a pandemic were beginning to emerge, which would have a massive impact on the airline industry. These findings provided support for Hypothesis 5, highlighting asymmetric propagation upstream vs downstream, as well as a more persistent impact on Boeing's suppliers compared to its customers.

*Table 7: Results of Boeing's Customers. Note: *p<0.10,**p<0.05,***p<0.01*

Event 1								Event 2							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[0, 3]	14	0.28	0.53	0.43	-0.03	50.00	-0.13	[0, 3]	14	-1.31	-1.13	-1.59	-1.53	64.29	-1.26
[0, 10]	14	3.03	2.81***	1.99	2.06**	7.69	3.08***	[0, 10]	14	-4.44	-2.32**	-4.55	-3.67***	81.25	-3.40***
[0, 15]	14	4.74	2.60***	3.94	2.76***	14.29	2.54*	[0, 15]	14	-0.11	-0.05	0.11	-0.30	50.00	-0.18
Event 3								Event 4							
	N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z		N	Mean (%)	t	Median (%)	Wilcox	% Neg	Z
[-1, 3]	14	0.58	0.45	0.88	0.51	28.57	1.44	[-1, 3]	14	-0.18	-0.14	0.39	0.31	50.00	-0.17
[-1, 10]	14	1.27	0.64	1.15	0.81	35.71	0.90	[-1, 10]	14	-1.30	-0.65	-1.45	-1.45	57.14	-0.71
[-1, 15]	14	2.27	0.95	1.57	1.57	28.57	1.44	[-1, 15]	14	-2.60	-1.09	-3.08	-2.09**	85.71	-2.85***

- *Research paper 2*

We now come to the hypotheses and results for the second research paper, which examined how global sourcing was impacted by U.S. tariffs during 2018-2019 time period. Global sourcing has various advantages such as lower product costs, foreign knowledge tapping, and access to foreign market directly. However, global sourcing also has been subject to various disadvantages, such as supplier relationship management and longer lead time. Therefore, both academic researcher and practitioners have advocated various global sourcing strategies to fulfill their corporate strategy to satisfy customer demands.

One unanswered question in OM literature is related to global sourcing dynamics, i.e., global sourcing patterns. According to firms' needs and capacities, different firms may adopt various global sourcing strategies to conduct international purchase. Accordingly, different firms' sourcing patterns may display diverse structures. Despite this, we can still conjure that firms adopting similar global sourcing strategies are likely to display similar sourcing patterns. For example, competitive Original Equipment Manufacturers (OEMs) like Apple and Samsung may have comparable sourcing of chips from time to time, and therefore their sourcing patterns may display similar trends or seasonality. In general, as literature has no prior evidence in this area, we leave this question as an open question, that is:

Research Question: How many groups can we find for U.S. importers based on their time series patterns?

After answering our first research question, we further investigated disruptive effects of tariffs for each pattern we can identify. Regardless of which sourcing strategy to use, one common observation is that firms build up inventories during or even before influential trade uncertainty. Previous found that firms tend to increase their inventory level to buffer potential supply disruptions, as well as empirical evidence that rising tariffs were positively associated with inventory holding of U.S. firms with direct suppliers from China. This finding suggested that there would be a sudden increase in sourced amounts during or even before tariffs came into effect. Moreover, this sourcing pattern would be reflected by the highest amount sourced in some time points in time series. After peak time of sourcing, we argued that two overall patterns might be observed for firms' time series of sourcing behaviors: (1) a pulse effect, which means that after a significant peak time of sourcing, firms reduce sourcing to pre-tariff level; and (2) a gradual reduction in sourcing amounts. As mentioned, theoretical

OM research consistently recommends dual or multiple sourcing (i.e., supplier diversification or dispersion) as a strategy to mitigate supply disruptions, including disruptive effects of tariffs. Empirical literature further tests whether dispersion of global sourcing could be a valid strategy to mitigate supply disruptions. From both theoretical and empirical evidence, we can conclude that some firms may effectively adopt dual or multiple sourcing to mitigate the tariff effects. Therefore, after significant sourcing amounts, their sourcing behaviors returned to pre-tariff levels. Besides this pattern, another possibility was that firms gradually reduce their sourced amounts. The original intention of imposing tariffs was to make production back to the U.S. Therefore, it was possible for firms to move production and sourcing back home. Current limited empirical evidence provides some support for this view. For example, in examining trade policy uncertainty, previous studies showed that firms with majority domestic sales indeed reduce their foreign supplier base, which suggested that these firms move production and sourcing back. Moreover, in investigating washing machines at the early stage of tariffs, it has been found evidence that firms move production back to U.S. to avoid tariffs. Based on these findings, we hypothesized that firms would gradually reduce their global sourcing amounts. Overall, for different groups identified, we hypothesize that there were two general trends in response to increasing tariffs. Therefore, we came to this hypothesis:

Hypothesis 1: In response to imposed tariffs, U.S. importers increased their sourcing amounts and had the following patterns:

- Some firms returned to their sourcing levels as before tariffs;
- Some firms had a gradual reduction of global sourcing after tariffs.

One important question is how importers' sourcing behaviors change in response to tariffs specifically imposed upon China. As most of tariffs were specifically to products from China, it is meaningful to see how this pattern changes in response to tariffs on Chinese products. Literature in this area provides various pieces of evidence. Based on previous studies, we can hypothesize that the sourcing patterns could be very similar with overall sourcing. Firms typically first built up inventory to buffer the disruptive effects of tariffs, and then either continued their sourcing as pre-tariff pattern or gradually reduced their sourcing due to switching suppliers from other foreign countries or moving production back. Accordingly, we had the following hypothesis:

Hypothesis 2: In response to imposed rising tariffs on Chinese products, U.S. importers increased their sourcing amounts and had the following two patterns:

- Some firms returned to sourcing level as before tariffs;
- Some firms had a gradual reduction of global sourcing after tariffs.

To answer our first research question, we applied our multivariate time series clustering algorithm. We chose the number of clusters, k, from 2 to 7. We relied on the seven Cluster Validity Indices (CVIs) to make a majority vote. The results showed that k=7 is the best result, as illustrated in the following Table 8.

*Table 8: Cluster Validity Indices (CVIs) for Clusters 2-7. Note: *p<0.10,**p<0.05,***p<0.01*

CVIs	Criterion	k=2	k=3	k=4	k=5	k=6	k=7	Vote
Silhouette	Maximized	0.118	0.099	0.098	0.090	0.078	0.090	k=2
Dunn	Maximized	0.187	0.211	0.241	0.184	0.244	0.290	k=7
COP	Minimized	0.559	0.531	0.523	0.505	0.496	0.487	k=7
Davies-Bouldin	Minimized	3.149	2.395	2.333	2.850	2.400	2.237	k=7
Modified Davies-Bouldin	Minimized	3.149	2.395	2.333	2.974	2.489	2.323	k=7
Calinski-Harabasz	Maximized	116.110	80.820	57.959	36.850	36.375	30.885	k=2
Score function	Maximized	0.000	0.000	0.000	0.000	0.000	0.000	No vote

Based on results from Table 8, we extracted seven time series from these seven clusters, focusing on the average number of amounts sourced for each month. In this way, we obtained seven time series for further intervention analysis. To conduct an intervention analysis, two steps are required. The first step is to identify the intervention time, i.e., March 2018 in our case. The second step for an intervention analysis is to determine the potential shape of intervention effect. Consistent with our hypothesis, the following Figure 9 illustrated the relevant shape for Hypothesis 1(a) and 1(b). This type of shape is also consistent with Hypothesis 2(a) and 2(b).

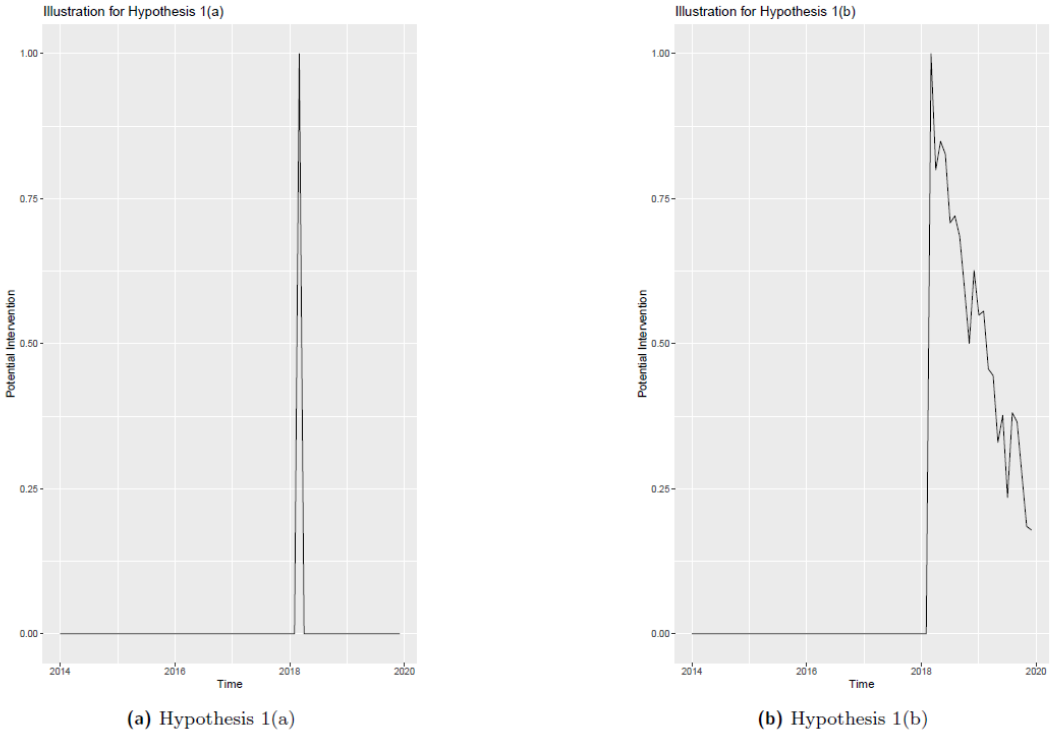


Figure 9: An illustration of Hypothesis 1(a) and 1(b).

To be consistent with Hypothesis 1(a), firms may significantly increase their sourcing first, and then return to pre-tariff sourcing amounts. Likewise, to be consistent with Hypothesis 1(b), firms may significantly increase their sourcing first, and then gradually reduce their sourcing amounts. To test our hypotheses, we will initially entertain models with these two patterns, using March 2018 at the cutoff time point. According to model fit, we will gradually revise models, which is consistent with Box-Jenkins methodology (Box et al., 2015). Specifically, we use forecast R package for our analysis. We will regress our time series in each cluster on the hypothesized intervention series. We will rely on characteristics of residuals for model diagnostic checking. We summarize the results as follows, in Table 9.

Table 9: Overall results.

	Series 1	Series 2	Series 3	Series 4	Series 5	Series 6	Series 7
H1a	No	No	Significant	Significant	No	Yes	Significant
H1b	No	No			No	No	
H2a	Yes	No	Yes	Significant	No	No	Yes
H2b	Yes	No	No		Yes	No	No

Overall from Table 9, for time series in cluster 1, although there was no significant intervention effect due to tariff, we found significant evidence that time series from China sourcing supported both Hypothesis 2(a) and 2(b). We found time series in cluster 2 had no disruptive effect from overall

sourcing and sourcing from China. For time series in cluster 3, we showed evidence in favor of increasing sourcing for one or more months, and then sourcing returns to normal pre-tariff level. Similarly for time series in cluster 4, there was a very sharp increase in sourcing starting before tariffs came into effect, which was different from time series in other clusters. For time series in cluster 5, we found significant evidence consistent with Hypothesis 2(b), showing that there is a gradual reduction of sourcing, with ups and downs from time to time. In contrast, time series in cluster 6 only supported Hypothesis 1(a), which meant overall sourcing had a significant increase in sourcing amounts and then returns to pre-tariff sourcing. Finally, time series in cluster 7 was similar with series in cluster 3. We found evidence that firms may increase sourcing level to hold inventory for multiple months before the sourcing returned to pre-tariff levels.

RESULTS TO BE PROUD OF:

1. THE PROJECT DEVELOPED EFFECTIVE TOOLS TO GATHER SC INSIGHTS
2. THE INVOLVED COMPANIES STARTED A PILOT IMPLEMENTATION OF THE DEVELOPED TOOLS
3. THE RESEARCH WAS ABLE TO DERIVE VALUABLE INSIGHTS ON DISRUPTION PROPAGATION IN NETWORKS OF FIRMS

DEMONSTRATOR 1

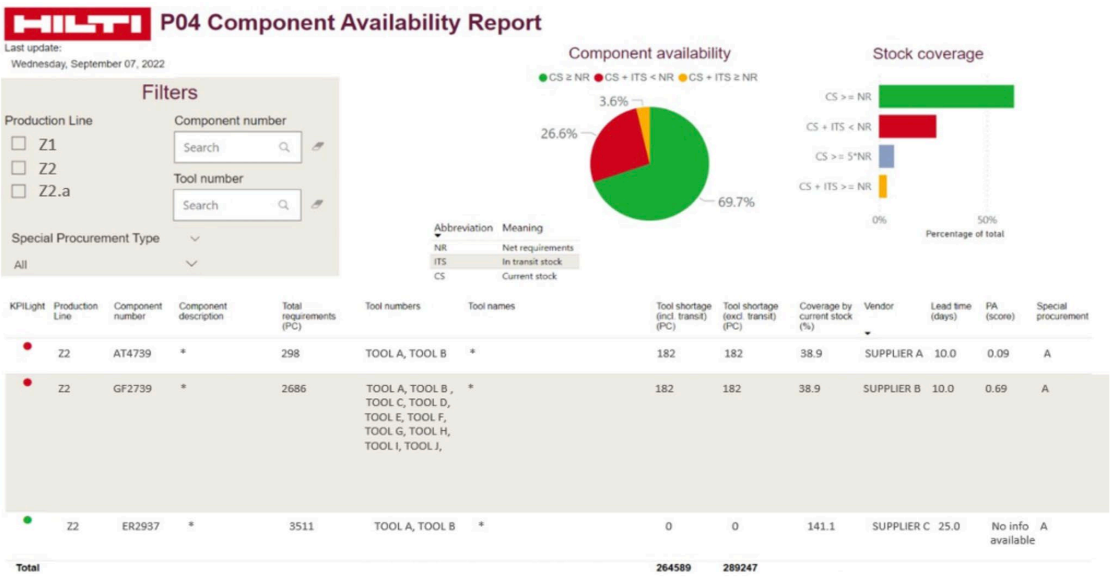
We developed a prescriptive module to support the expediting process for one of the customers of Bright Cape. The module has been integrated in the Celonis tool. It is able to predict which items will be delivered late and to compute an expedite score who support the human users in determining which supplier to call first.

Client	Purchasing Document	Item	Planned delivery date	Predicted delivery date	Predicted days overdue	New Expedite Score	Original Expedite Score
411	5506262171	00001	2022-08-08	2022-07-25	-14	10	10
411	5506303998	00001	2022-10-12	2022-09-13	-29	10	10
411	5506307869	00001	2022-09-20	2022-09-29	9	10	10
411	5506323040	00001	2022-10-05	2022-09-26	-9	10	10
300	4502278952	00020	2022-09-02	2022-08-15	-18	10	10
300	4502278952	00030	2022-09-02	2022-08-20	-13	10	10
300	4502286017	00010	2022-10-28	2022-11-16	19	9.8	6.6
300	4502308401	00010	2022-10-17	2022-10-17	0	9.8	9.8
300	4502308402	00010	2022-10-17	2022-10-17	0	9.8	9.8
300	4502308403	00010	2022-10-17	2022-10-20	3	9.8	9.8

Screenshot showing the priority list updated according to the predicted delays.

DEMONSTRATOR 2

We developed a dashboard able to take as input BoM and inventory data to quantify the material availability at a given moment in time for the Hilti S&Op process. The tool also support a limited scenario analysis, allowing the user to investigate which end-components are affected the most by the lack of raw components.

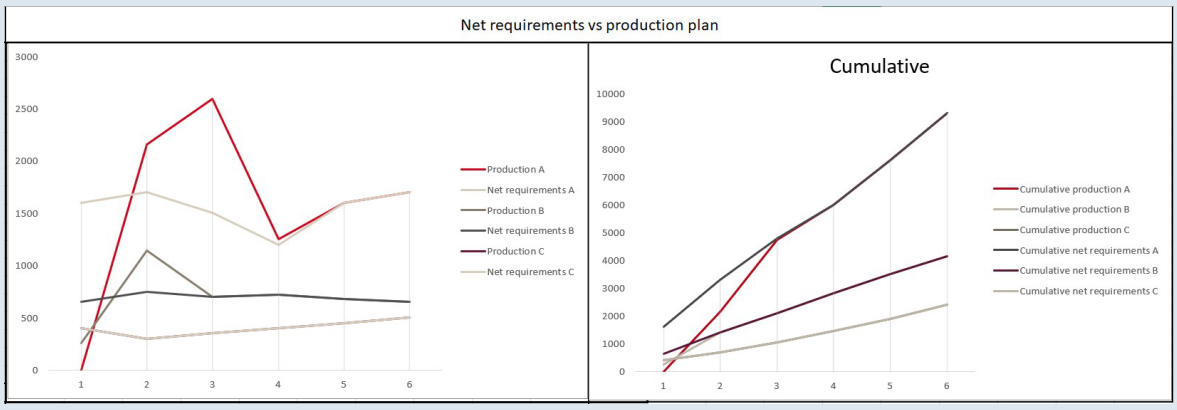


Screenshot showing the overview window of the component availability tool

DEMONSTRATOR 3

We developed a too aimed to support scenario analysis within the S&OP process of Hilti. The tool aims to support decisions related to determine suitable mitigation strategies to deal with disruption affecting labour-force, machines or material availability. The tool allows the user to determine several parameters related to material, work-force and machines availability and optimizes the recommended actions based on the overall cost.

Total costs = 916053,80 CHF	Periods				
Costs (in CHF)	1	2	3	4	5
Total purchasing costs	55280	159448	148970	109252	121650
Total day shift costs	856	4800	4800	3201	3756
Total night shift costs	0	33,60	372	0	0
Total idle costs	2144	0	0	0	0
Total component inventory costs	695,20	237	0	0	0
Cost of lost sales "A"	80000	57200	2700	0	0
Cost of lost sales "B"	39400	0	0	0	0
Total costs	176335,20	215718,60	156842	112453	125405
Decision variables					
Production "A"	0	2156	2590	1254	1600
Production "B"	256	1144	700	720	680
Production "C"	400	300	350	400	450
Component "a" required	1680	16800	16800	10270	11850
Component "b" required	12730	16000	16000	13470	14800
Component "c" required	500	1656	2590	1254	1600
Component "d" required	656	1444	1050	1120	1130
Component "e" required	2512	3788	3150	3440	3610
Day shift hours required	57,07	320	320	213,4	250,33
Night shift hours required	0	1,87	20,67	0	0
Idle time	142,93	0	0	0	0
Inventory "b"	10170	3950	0	0	0
Inventory "c"	500	0	0	0	0
Backlog "A"	1600	1144	54	0	0
Backlog "B"	394	0	0	0	0



Screenshot showing some of the output windows of the scenarios

EXPERIENCES

The project managed to achieve most of the goals determined at the beginning.

OPEN INNOVATION

The consortium went through some changes for personnel reasons, which resulted in two companies leaving the project before the end. Nevertheless, other companies were interested in joining the research, which allowed us to carry out the research as planned. The involved companies were dedicated and committed to the research and were satisfied with the developed tools. Trial implementations of the developed tools are currently carryed out by these companies.

DINALOG AND TOPSECTOR LOGISTICS

While the project addressed different dinalog topsector themes (see previous sections), we did not establish a formal collaboration with other Dinalog projects.

MASTER THESES AND RESEARCH PAPERS

Four master theses were performed in relation to the project. Each of them focused on a case study, described in the previous section. Furthermore, we submitted two research papers describing the analysis carried out on the public datasets mentioned in the project setting section.

MASTER THESES- DOW, BRIGHTCAPE, HILTI

Wthin the project, four master theses have been conducted on real-world case studies within the involved organizations. A summary is presented below:

- Analyis of the ripple effect from the Suez canal disruption on a portion of the Dow supply chain;
- Development of a tool for early detection of delivery delays and for supporting decisions in the expediting process, for a mininig company client of BrightCape
- Development of a material availability dashboard for Hilti S&Op process
- Development of a scenarios analysis tool for Hilti S&Op process

A more detailed description of the challenges of the above mentioned case studies and the developed methods can be found in the Results Section.

VISION OF THE FUTURE

The project highlighted the crucial importance for companies to be prepared in detecting and reacting to disruption. In particular, it demonstrated how evidence-based methods and tools can support companies in gathering relevant insights to enhance transparency in their chain and improve their mitigation strategy. Firms that have better visibility of the geographic diversity of their supply chain are better prepared to take nearshoring and reshoring decisions. These decisions can lead to significant reduction in CO2 emissions. Furthermore, with improved visibility and the disruption mitigation actions prescribed by this research, these firms will be able to build resilient supply networks. This has a direct relationship with the market value of these firms, which will contribute to the growth in GDP of the Dutch economy.

In order to further proceed in this direction, actions are needed to strenghten the collaboration within supply chains. A crucial element to achieve this is to develop novel solutions enabling a more efficient and transparent exchange of information between the different tiers. At the same time, additional research is needed to better understand how humans interact with AI tools and how to succesfully promote the adoption and the usage of these tools.

FOLLOW UP ACTIVITIES

The research also shown some important limitations that need to be addressed to move further. Among them, we higlight:

- Data quality and availability. The development of data-driven techniques requires the availability of quality data describing the interactions happening within the supply chain among different partners. This, in turns, requires the development of techniques and platforms enabling such a data sharing while guarantiing security and privacy. At the same time, actions are needed to establish a collaborative environment promoting trust within the supply chain.
- Human-technology interaction. Currently, the adoption of AI-based techniques is hampered by a lack of trust of the human users towards these techniques. More research is needed to ensure that the actions suggested by these tools are comprehensible and trustwhorthy for the users, as well as to understand how to improve the interaction of the users with the system.

“THE RESEARCH ALSO SHOWN SOME IMPORTANT LIMITATIONS THAT NEED TO BE ADDRESSED TO MOVE FURTHER. AMONG THEM WE HIGLIGHT: - DATA QUALITY AND AVAILABILITY - HUMAN-TECHNOLOGY INTERACTION”

PROJECT PARTNERS

EINDHOVEN UNIVERSITY OF TECHNOLOGY PARTNER

TU/e conducted and managed the scientific research. The research team at the TU/e has specific expertise in inventory management, risk management and business process management.

CHAINSTOCK

Chainstock is the SME partner that provides services for firms with multi-echelon supply chains. They helped the TU/e in the scientif ic research and be active in the valorization and im plementation of the research findings. They were involved in the Dascovimi project. Chainstock has many years of experience in providing consulting services to large focal firms with complex supply chains

HILTI AG

Hilti is a large focal firm in the tools and chemicals industry and has numerous suppliers and customers. Hilti has a large global supply network; they are aware of the challenges faced by firms in disruptions. Their S&OP processes provided two case studies to develop and test our tools and techniques.

NEWAYS

Neways is a large focal firm in the Electronics manufacturing sector. They were involved in the Dascovimi project and continued to work with the research team on visualization and disruption mitigation actions.

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