

# How to Predict Disruptions in the Inbound Supply Chain in a Volatile Environment

Andréas MALMSTEDT<sup>a</sup> and Jenny BÄCKSTRAND<sup>b1</sup>

<sup>a</sup>Group IT, Ericsson AB, Kista, Sweden

<sup>b</sup>School of Engineering, Jönköping University, Jönköping, Sweden

**Abstract.** The most common solutions to protect the supply chains for disruptions are increasing inventory, adding capacity, and using multiple suppliers. While these approaches in general prove to solve the disruption problem, they come with a negative effect on cost per product and cost of capital. In a highly volatile demand environment with fast pace changing technology, increasing inventory can constitute a big risk for obsolescence, hence additional measures are needed to create a competitive business advantage with such a supply chain. Furthermore, when competing about the same sources, as in the case of semiconductors, Operations Executives need to be able to respond fast when supply issues occur, in order to minimize the potential impact from a disruption. The ability to react and response to a disruption is enhanced with Supply chain risk tools utilizing the most recent technologies, such as Control Tower solutions enabling End-to End monitoring and transparency. However, even with the help of such technology, the decision maker will still be reactive and can merely respond to occurrences. To reach the next level of responsiveness, additional layer of intelligence is needed in the supply chain solution. From the available literature about Supply Chain Resilience, and similar advanced supply chain solutions, we can conclude that the main focus of research has so far been on the demand side, i.e., how to enhance forecast management. There are thus few practical and academic contributions on how to manage the supply side or more precise on how to manage the Inbound Supply Chain in a volatile business environment. The purpose of this paper is to investigate what factors that are crucial to regard when creating a proactive and responsive Inbound Supply Chain.

**Keywords.** Inbound Supply Chains, Responsiveness, AI, Machine learning, Algorithms

## 1. Introduction

In the recent decades, the focus for most Operations Executives have been to optimize the cost structure of their supply chains. The recipe has been Lean and Global supply chains. As a consequence, the length and complexity of global supply chains have increased, and the upstream visibility has decreased [2]. As a result, a large multinational company can have hundreds of tier-one suppliers from which it directly purchases components. Each of those tier-one suppliers in turn can rely on hundreds of tier-two suppliers [1], see Figure 1. Hence, today's supply chains are in fact dynamic networks of interconnected firms and industries, contributing to a volatile, complex, uncertain, or even ambiguous situation [3]. If these supply chain networks are not fully vetted, both

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<sup>1</sup> Corresponding author: Jenny Bäckstrand, School of Engineering, Jönköping University, Box 1026, 551 11 Jönköping Sweden; E-mail: jenny.backstrand@ju.se.

vertically and horizontally, this can constitute a risk for unintended consequences according to [2] and [4]. One direct consequence could be lack of visibility and hence late detection of a disruption.



**Figure 1.** Supply chain network-multi tier network. [1].

average industry now can expect a supply chain disruption lasting a month or longer to occur every 3,7 years, and that will have implications on both revenue and costs.

Since the year 2000 there has been multiple events disrupting the supply chains such as the famous factory fire in Mexico which affected Ericsson & Nokia, Flooding in Thailand affecting the standard electronics categories, Hekla affecting global logistics, Earthquake in Japan affecting the automotive and semiconductors, Global allocation of Electronics in 2018 and Covid-19 which had its biggest impact in recent memory. In addition to that, the recent trade and political events make it even more complex to operate, which has been widely covered in e.g., *The Economist* October 2021.

These crises have exposed the weaknesses of global supply chains optimized for cost efficiency rather than resiliency, this problem is intensified in organizations with poor visibility of complex, multitier supply bases [7]. Put more strongly, these risks have not been fully priced in the revenue and cost calculation.

Common solutions to protect the supply chains for disruptions are increasing inventory, adding capacity, and using multiple suppliers [see for example 2, 8, 9]. This works well in low to medium high volatility for products with continuous demand where the extra buffer or a second supplier could protect the supply chain. Although, this comes with an impact on cost per product and cost of capital. In a highly volatile demand environment with fast pace changing technology, buffer dimensioning is difficult to get right; which parameters should be included? Which is the right buffer level? Another challenge is when the buffer is in place, the technology requirement might already have changed, i.e., advanced semiconductors with lead time of more than 40 weeks, leading to obsolescence or if standard electronics are used in modules where the demand situation have changed, then allocated material is being tied up in wrong products which could lead to stock-outs. From a multisource perspective, introducing more than one supplier during the ramp up period requires more R&D resources and might influence the time to market and the associated cost. Hence, additional measures are needed to create a competitive business advantage with such a supply chain. Furthermore, when competing with competitors about the same resources, as in the case of semiconductors or standard

There could also be indirect impact from disruptions which propagate through the supply chain which Ivanov, Sokolov and Dolgui [5] call ripple effects. These ripple effects can also be increased in large supply chain networks [6]. Since the main focus of the supply chain design has been cost efficiency with lowest possible cost per unit, where lean and just-in-time principles have cut spare capacity and buffer stocks to a minimum in many sectors, the production networks are not always designed to operate in a world where disruptions are regular occurrences. According to Lund et al. [2] the

electronics, Operations Executives need to be able to respond faster than the competition when supply issues occur, in order to minimize the potential impact from a disruption. During the first part of 2021, there have been numerous reports of production halt and product launch delays due to the lack of semiconductors and global allocation, which showcase the need of improved responsiveness [10].

The ability to react and response to a disruption is enhanced with Supply chain risk tools utilizing the most recent technologies, such as Control tower solutions enabling End-to-End monitoring and transparency [2]. However, the decisions supported by these tools will still be reactive. To reach the next level of responsiveness, an additional layer of intelligence is needed in the supply chain solution. We can conclude [11] that the main focus of research has so far been on the demand side, i.e., how to enhance forecast management. There are thus few practical and academic contributions on how to manage the supply side or more precise on how to manage the Inbound Supply Chain in a volatile business environment and we will hence focus on the algorithms used in AI technology for supporting inbound supply chain decisions in a volatile business environment.

The purpose of this paper is to investigate what factors that are crucial to regard when creating a proactive and responsive Inbound Supply Chain.

The research questions (RQ) are: RQ1: *What building blocks are used to create a resilient and responsive supply chain?* And RQ2: *How can quantitative methods be used to augment disruptions in inbound material flows?*

The expected result is the identification of factors relevant when developing an AI-algorithm supporting decisions for a predictive Inbound Supply Chain in a volatile demand environment with fast pace changing technology.

To provide answers on the research questions the paper is organized as follows. In the next section the methodology approach is presented. This is followed by a literature review of supply chain resilience and supply chain building blocks. Then, an empirical example from our case company is presented, followed by an analysis. The paper ends up with a conclusion on if quantitative methods can be used to augment disruptions in inbound material flows in a volatile and complex business environment.

## 2. Method

In order to fulfill the purpose and answer the research questions, we have combined a literature study with a retrospective and longitudinal analysis of data collected in a single case study between 2020 and 2021. The unit of analysis that have been studied is supply chain disruptions, the responses of the studied organization to these disruptions, and the effects. One of the authors is employed at the case company and have been involved in the project the single case study is based on. The empirical data is hence first-hand information. The theoretical basis is built on the areas supply chain risk, supply chain resilience and the definition of volatile environments to complement the areas studied and the gaps identified in the empirical study. The results also include results from a proof-of-concept where a machine learning model has been developed with the purpose to augment disruption detection in a volatile inbound supply chain at the case company.

### 3. Theory

The theoretical framework is built on factors and methods to increase inbound supply chain resilience, and characteristics of a volatile environment.

#### 3.1. Supply chain Resilience

Supply-chain risks can, as earlier described, cause severe supply-chain problems, causing unanticipated changes in flow due to disruptions or delays. This may result in losses of revenue and incur high recovery costs [5]. Due to its nature, the frequency of disruptions varies as well as the magnitude of the problem in size and duration.

Organizations that manage these risk events better than others share one common trait: resilience, according to [12]. Supply chain resilience is defined as:

*“The capacity of a system (supply chain) to return to its original state or move to a new, more desirable state after being disturbed”* [13].

Hence, the question arises – How do you build a resilient supply chain? When reviewing the literature in this field a couple of common factors emerge.

##### 3.1.1. Building resilience through inventory and extra capacity

The first and most frequent tactic is keeping Inventory or Extra capacity in the supply chain according to [12]. The challenge with buffers, of course, is that they are expensive and hard for individual companies to justify. The question therefore becomes how to position and dimension the supply chain reserves in order to balance impact on profit and loss and cash flow. [8] and [2] illustrate in their work on how Dell, Toyota and other leading manufacturers have excelled at identifying and neutralizing supply-chain risks through a delicate balancing act: keeping buffers and extra capacity at appropriate levels across the entire supply chain in a rapidly changing environment. Moreover, they argue that organizations can prepare and mitigate delays by "smart sizing" their capacity and inventory. Chopra and Sodhi [8] and others provide the methods but not on how to do it "smart". Extra capacity is justified when launching a new product or before entering a new market. One strategic question here is if the extra capacity should be internal or external. Sometimes a manufacturing expert might be able to absorb the "extra" cost since it has other customers. Another common strategy is postponement which [12] argue for in their work.

##### 3.1.2. Risk mapping/multisource

Furthermore, [8] recommend a powerful What if? exercise called stress testing and often referred to as supply chain risk mapping to identify potentially weak links in the supply chain which also [13] recommend. The outcome from this risk mapping can provide some help in which is the best mitigation strategy whether to keep buffer or capacity. The outcome of the risk mapping can also be applied to the inbound supply chain. One of the most important factors in building more redundancy into supplier networks is multisource. Relying on a single source for critical components or raw materials can be vulnerability [13]. To identify, qualify, and onboard backup vendors comes at a cost, but it can provide much-needed capacity if a crisis strikes.

Additionally, further analysis can be beneficiary to review if some of the risk be pushed upstream in the supply chain where the number of differentiating factors is less? Perhaps a supplier with proven flexibility should be considered in combination with a

volume supplier? When reviewing the supplier strategy, options for Multisource should be considered or used in combination with depending on the network design, cost of stock out and time to recovery from the disruption. This is why companies such as Samsung Electronics Co. Ltd. always aim to have at least two suppliers, even if the second supplier only provides 20% of the volume [9]. Supplier Management of critical suppliers should also be included in the action plan [2, 13]. Christopher and Peck [13] also mean related to supplier management that a high level of collaborative working across supply chains can significantly help mitigate risk. The flooding in Thailand affecting the standard electronics categories and the Earthquake in Japan affecting the automotive and semiconductors also illustrated the risk of county of origin (COO). Hence, Operations Executives also need to review where the factories are located since many suppliers have their factories in same regions especially for single source [7].

### *3.1.3. Building resilience through containment*

Chopra and Sodhi [9] suggest two additional strategies for reducing supply chain risks through Containment (1) segmenting the supply chain or (2) regionalizing the supply chain. Segmenting: For high-volume commodity items with low demand uncertainty, it is recommended to have a supply chain with specialized and decentralized capacity. For fastmoving basic products (typically, low margin), it may be worthwhile to source from multiple low-cost suppliers [9]. This reduces cost while also reducing the impact of a disruption at any single location, because other suppliers are producing the same item, which is the aim with multisource. For low-volume products with high demand uncertainty (typically, high margin), companies can take a different approach and keep supply chains flexible, with capacity that is centralized to aggregate demand.

In addition to segment products with different risk characteristics, Operations Executives should consider treating the more as well as the less predictable aspects of demand separately. One example from [9] is the approach used by many utilities' companies employing low-cost coal-fired power plants to handle predictable base demand, while shifting to higher-cost gas- and oil-fired power plants to handle uncertain peak demand [14]. Having two or more sources of supply reduces the impact of disruption risk from a single production facility.

Regionalize the supply chain: Containing the impact of a disruption can also mean regionalizing supply chains so that the impact of losing supply from a plant is contained within the region by having localized production and or distribution centers [9]. During such event, capacity can be utilized from another region to manage the disruption. An earthquake in Japan showcased the need regionalizing production also at lower tier in the supply chain, but also, the vulnerability to technology clusters [7].

### *3.1.4. Building resilience through modular design*

Another way to achieve supply chain resilience is to design products with common components, Modular Design and by that reducing the number of customized part numbers in the main product [2]. The Auto industry is one of the most matured examples having implemented modular manufacturing platforms that share components across product lines and production sites [2]. This obviously reduce the complexity is the supply chain and also enable cost of scale. Moreover, manufacturing platforms also enable regionalizing [9]. The target is to be able to produce a product at any of the qualified production sites with robust performance and quality. This allow for product to be moved across the globe if needed, in short time.

### 3.1.5. Building resilience through technology/increased visibility

During the most recent time Global manufacturing has just begun to adopt a range of technologies such as analytics and artificial intelligence, and digital platforms to enable a more resilient supply chain [2]. According to Goering, Kelly and Mellors [15] most companies are still in the early stages of their efforts to connect the entire value chain with a seamless flow of data. However, digitalization can deliver major benefits to efficiency and transparency that are yet to be fully realized.

The role of supply chain visibility in managing supply disruptions is highlighted by Brandon-Jones et al. [4] who argue that real time data from supply chain partners can enable early identification of disruptions enabling firms to mitigate the disruptions before they cause any disruptions to the flow of goods or services. Emerging examples are given by Ivanov and Dolgui [14] and others who show that supply chain resilience can be improved with the help of data analytics and big data.

One practical example to illustrate this is given by [2]; Procter & Gamble has developed a control tower system for End-to-end supply chain monitoring. It integrates real-time data, from inventory levels to road delays and weather forecasts, for its own plants as well as suppliers and distributors. When a problem occurs, the system can run scenarios to identify the most effective solution on how to mitigate the problem.

Supply chain control tower can also be empowered by a detailed sub tier mapping to identify hidden relationships that invite vulnerability and by that increase the supply chain visibility. Mapping involves engaging suppliers to understand their global sites and subcontractors, as well as knowing which parts originate or pass through those sites.

This can be done by utilizing supply chain risk platforms which can be integrated into the control tower. Utilizing this capability detection of events, identifying risk, analysis of the potential impact can be reduced down to minutes according to [16]. In Figure 2 an example of a “Eventwatch”, a module in a Supply chain risk platform, is illustrated with the notice of power outage impacting a supplier.

Equipped with Supply chain control tower, more precise mitigations activities can be executed given the detail supply chain mapping and historical data of similar events and actions.

Ivanov and Dolgui [14] take this one step further in their work where they present how the applications from a traditional supply chain control tower can be enhanced with simulation and analytics to create a digital twin and thereby increase the supply chain resilience with a faster detection of potential disruptions. This is in line with what Craighead et al. [17] who emphasize the role of disruption detection, and

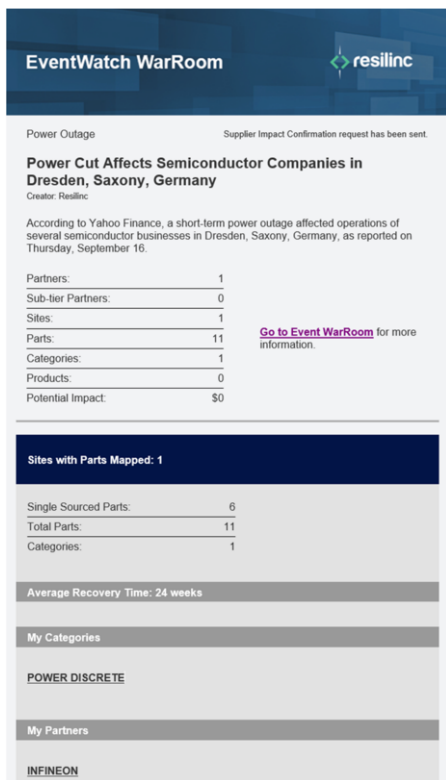


Figure 2. An example of an Eventwatch notice

Ambulkar, Blackhurst and Grawe [18] the role of alertness of firms to disruptions in achieving supply resilience. [19, 20] also emphasize that data analytics is an enabler for fast decision making. Manhart, Summers and Blackhurst [21] expand this when they also highlight the importance of analyzing the changes in the data or trends.

With the help of AI, organizations can detect potential disruptions by building an algorithm based on demand data, financial and supplier performance data. Furthermore, Diagnostic analytics can also help to find the causes of the disruptions and prescriptive analytics can be used to optimize the choice of mitigation activity given the available options. A digital twin can enable a more dynamic sensing capability and further enhance the robustness of the supply chain.

### 3.2. Building supply chain resilience

Summarizing all the measures and actions taken to build a resilient supply chain, the following table can be concluded, see Table 1 [11].

**Table 1.** Methods and tools used to create a resilient supply chain

Supply chain building blocks for a resilient supply chain	References
Supply Chain Risk Mapping	Christopher & Peck (2004), Chopra & Sodhi (2004), Lund et al., (2020).
Inventory & Capacity Buffer	Chopra & Sodhi (2004), Lund et al., (2020), Sheffi (2005).
Multisource	Christopher & Peck (2004), Chopra & Sodhi (2014), Lund et al., (2020), Sheffi (2005), Shih (2020).
Containment	Chopra & Sodhi (2014).
Modular designs	Lund et al., (2020).
Supply chain control tower	Goering et al. (2018), Ivanov & Dolgui (2020), Linton & Vakil (2020).

Thereby, research question 1 (RQ1) is answered.

## 4. Empirical example – proof-of-concept

A proof-of-concept project was conducted at the case company to investigate if quantitative methods could be used for predicting disruptions in the material flow for a high-tech company operating in a volatile business environment. The research questions were inspired by what Volvo Trucks and SAS developed in order to reduce the down time for a truck by predicting when maintenance is needed (in order to avoid a disruption).

Material is usually constituting the constraint when managing a mix or volume in the supply chain. With a proactive review of the material situation, one can see signs, patterns, correlations that from a historical perspective usually indicate a high risk for disruption and then initiate proper activities to mitigate the potential issue. A hypothesis was formulated – Would it be possible to apply quantitative methods to predict and automate this analysis?

To investigate this hypothesis, a team was assigned to deliver a proof-of-concept, consisting of a Product owner, a Lead Data Scientist, and a Data analyst. The team started by analyzing best practice within the procurement department by conducting deep interviews of some of the Senior Supplier Managers. This is in line with [22].

One early idea was – is it possible to mimic the way the senior Supplier Manager analyses their component situation? What do they consider? Why? When do they do it? Which data to they use? From the interview with the Supplier Managers, the team found out that there were patterns that the Supplier Managers looked for. Warning flags could be Single source, long lead-time devices, newly introduced devices with high ramp up plans, components or supplier that usually constitute issues in volume ramp, components with high ratio in new products, and components in products with significantly change in production plans.

This formed ideas on which data that was required to build a model that could predict and automate this analysis. To narrow down they scope, the team chose one semiconductor supplier for the proof-of-concept. A supplier with components used by many products (both high runner and low runners) and with years of history. Thanks to existing data, they could quickly gather historical data on material forecasts, forecast response, production plans, material characteristics such as lead-time, number of suppliers, age etc. This formed the first Analytics Base Table (ABT), see Table 2.

**Table 2.** Analytics Base Table

<b>Target variable</b>	<b>Description variables</b>	<b>Volume variables</b>
Balance of supply for a part number	Category	Buffer
	Product unique	Order intake
	Company unique	Forecast response
	Platform common	Forecast change
	Platform	
	PLCM	
	Volume split	
	Leadtime	
	Internal capacity	
	Number of products	
	Number of customers	
	Number of suppliers	

From the ABT feature engineering was performed using Databricks and after some rounds of modeling, following guidelines from [23], a base model was created in python based on historical data from 2018-2020. Decision tree was chosen as the best suitable model, after several model iterations, which is a decision tree-based machine learning model [24]. Decision trees are supervised learning methods used for both classification and regression tasks [25]. The data science problem here is in fact a classification problem. The target variable was: *will there be a shortage in 4 weeks for given material?* The variables used were: 0 = No shortage and 1 = Shortage.

One important note here is that the data used was imbalanced data since 80% of the materials never had shortage, and 6% shortage rate of the remaining 20% materials. When optimizing the model, class weights were applied to adjust the cost penalty with the assumption that a cost of false negative is much higher than the cost of false positive, meaning the cost of missing a disruption is higher than the analyzing cost of an additional signal. The result of the model is shown in the confusion matrix in Table 3. Confusion matrix is a summary of prediction results on a classification problem. It provides the insight into error being made by the classifier and also on what types of error [23].



**Table 3.** Confusion matrix of prediction results

	Confusion Matrix	
	Pred 0	Pred 1
True 0	2923	799
True 1	44	64

Based on historical data of actual shortages, the Decision tree model can catch 64 shortages out of 108 (59,3% recall), with 7,4% precision. The table is showing the performance during the period of 12 weeks during 2020.

## 5. Analysis

In the literature reviews performed by [25] and [26], the most frequent applications of machine learning (ML) in supply chain management are presented. From their reviews we can note that ML and big data analytics have increasingly been used for supplier selection, sourcing risk management, production planning and control, inventory management, demand forecasting and demand sensing. There are however not so much written on predicting disruptions in material flow.

In many SCM problems, it is assumed that capacity, demand, and cost are known parameters. However, this is not the case in practice as there are uncertainties arising from variation demand, supplier performance, transportation lead time, supplier lead time etc. [26]. Demand uncertainties in particular, have great influence on supply chain performance with widespread effects on production scheduling, inventory planning, and transportation. Hence, it is understandable that demand forecasting is more broadly researched.

Going deeper and reviewing supply chain management in semiconductor manufacturing, as in the proof-of-concept, [27] state the significant challenges that arise from the presence of long throughput times, unique constraints, and stochasticity in throughput time, yield, and customer demand.

In model development choosing the right features is an important element of effective algorithms. A feature is a numeric representation of raw data [28]. A good way of defining features is to identify the key domain concepts and base the features on these concepts [28].

Comparing the features used in the model (Table 2) with the factors from the resilience study in research question 1 (Table 1), we can see high alignment with the features used and factors derived from the supply chain building blocks. From that comparison, we can conclude that the factors derived from the Supply chain building blocks for a resilient supply chain is relevant in building a quantitative model, see Table 4.

**Table 4.** Factors in building a quantitative model derived from SC building blocks for a resilient SC in building a quantitative model

Supply chain building blocks for a resilient supply chain	Translated into Factors	References
Supply Chain Risk Mapping	Country of Origin, back end and front-end locations, lead-times.	Christopher & Peck (2004), Chopra & Sodhi (2004), Lund et al., (2020).
Inventory & Capacity Buffer	Buffer size, buffer target, capacity,	Chopra & Sodhi (2004), Lund et al., (2020), Sheffi (2005).
Multisource	Number of suppliers	Christopher & Peck (2004), Chopra & Sodhi (2014), Lund et al., (2020), Sheffi (2005), Shih (2020).
Containment	Number of products, Volume per region/customer, Number of suppliers per region.	Chopra & Sodhi (2014).
Modular designs	Volume per module	Lund et al., (2020).
Supply chain control tower	Locations of disruptions, frequency of disruptions, duration of disruptions, size of disruptions	Goering et al. (2018), Ivanov & Dolgui (2020), Linton & Vakil (2020).

Analyzing the model in the proof-of-concept, the team used a decision tree (DT) model. [25] conclude in their review of ML-algorithms that a general use of DT models is in fact classification problems. The advantage of the DT model is the easy calculation, its capability to assess an item with different features and having strong interpretability. On the other side of the coin is that it is easy to be over-fitting.

Other common models for classification problems are random forecast, K-means, that are a bit more complex, and DT can hence be a logical choice for an initial model. From the confusion matrix we can conclude that the recall-rate is acceptable, and the model generates a lot of signals that need to be processed. However, there is signal value in the model which demonstrate that quantitative methods can be used in augment disruption detection, but for practical relevance the precision needs to be improved. Hence, we conclude a more relevant usage of this model could be to augment and automate the analysis of critical material, material with shortage or material with high risk of shortage. The outcome of the model can then be analyzing further by a Supplier Manager. If the model is updated on a monthly interval the penalty of the low precision can be mitigated. The combination of signals from the model and a second review from the user can also increase the trust and thereby the adoption of the model.

## 6. Conclusions

Given the situation with more frequent disruptions, we argue the need for smart execution of building resilience in the supply chain. Building a resilient supply chain is a long-term design effort. But it can be combined with building blocks that can gain effect in the short-term while designing the coming releases of the supply chain resilience.

What we can conclude is that companies have many different options to build resilience which our review shows. The challenge is time to commit before the issues occur. Once in a crisis there is usually limited time available for changing the supply chain design, implementing a new technology solution etc. Given the increased frequency of disruptions the implementation lead-time and the sequence order of the

building blocks become important. We have previously suggested an order to achieve increased resilience quickly and an approach for further investments [11]. With a smart use of capital, fast detection of disruptions together with proper responses, the supply chain can become a competitive advantage. To reach the next level of responsiveness, we suggested that additional layers of intelligence are needed for a predictive supply chain solution, especially for volatile and complex business environments. Hence, the purpose of this paper was to investigate what factors that are crucial to regard when creating a proactive and responsive Inbound Supply Chain. The first research question was formulated as: *What building blocks are used to create a resilient and responsive supply chain?* This was answered and compiled in Table 1. Comparing the features used in the model with the factors from the resilience study in research questions 1 we can see close relationships. From that comparison we can conclude that the factors derived from the Supply chain building blocks for a resilient supply chain is relevant in building a quantitative model.

The second research question was formulated as: How can quantitative methods be used to augment disruptions in inbound material flows? This was answered by analyzing a proof-of-concept project executed at the case company. From the proof-of-concept, we can conclude that it is possible to develop prediction model for material disruptions. However, the practical use of the model is limited. The recall is acceptable, but the precision is rather low which means that a lot of signals need to be processed which can hinder the adoption of the model from the end-users.

For this paper we can conclude: As established in the introduction there are not much written on predicting disruptions in material flows, nor practical suggestions on best practice in developing a model for actual business use. This paper has contributed to cover this research gap by establishing that:

- Tools are in place to develop predictive models
- Resilience factors provide a good foundation for input to which factors should be considered in modeling
- It remains to make predictive models more practical to insure a wider adoption.

### 6.1. Further research

Reviewing the outcome from the predictive model presented in the proof-of-concept, further research is needed to find appropriate variables to enhance the model with feature engineering to improve the precision of the model. The proof-of-concept is done based on analysis of one broad semiconductor supplier. We would recommend investigating if the model can be scaled into several suppliers within the same category or into a complete cluster of categories. In that research, it needs to be investigated if the same model can still be used or if it would require additional features or another machine learning model.

Additional research is also needed to ensure that a predictive model can be used in practice. For example, which threshold in terms of precision is required to enable high usage of the models?

## References

- [1] Buckley J, Joyce P. Secure Supply Chain: 5G pilot Executive Summary: Deloitte AB; 2018.
- [2] Lund S, Manyika J, Woetzel J, Barriball E, Krishnan M, Alicko K, Birshan M, George K, Smit S, Swan D. Risk, resilience, and rebalancing in global value chains. McKinsey Global Institute. 2020.
- [3] Bennett N, Lemoine J. What VUCA really means for you. Harvard business review. 2014;92(1/2).
- [4] Brandon - Jones E, Squire B, Autry CW, Petersen KJ. A contingent resource - based perspective of supply chain resilience and robustness. Journal of Supply Chain Management. 2014;50(3):55-73.
- [5] Ivanov D, Sokolov B, Dolgui A. The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. International Journal of Production Research. 2014;52(7):2154-72.
- [6] Lee HL, Padmanabhan V, Whang S. The Bullwhip Effect in Supply Chains. Sloan Management Review. 1997;38(3):93-102.
- [7] Shih W. Is it time to rethink globalized supply chains? MIT Sloan Management Review. 2020;61(4):1-3.
- [8] Chopra S, Sodhi M. Supply-chain breakdown. MIT Sloan management review. 2004;46(1):53-61.
- [9] Chopra S, Sodhi M. Reducing the risk of supply chain disruptions. MIT Sloan management review. 2014;55(3):72-80.
- [10] Alsop T. Global chip shortage 2021 - statistics & facts 2021 [updated Apr 26, 2021. Available from: <https://www.statista.com/topics/7797/global-chip-shortage/>.
- [11] Authors. Hidden for anonymity. 2021.
- [12] Sheffi Y. Building a Resilient Supply Chain Harvard Business Review - Supply Chain Strategy. 2005:1-4.
- [13] Christopher M, Peck H. Building the resilient supply chain. 2004.
- [14] Ivanov D, Dolgui A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Production Planning & Control. 2020:1-14.
- [15] Goering K, Kelly R, Mellors N. The next horizon for industrial manufacturing: Adopting disruptive digital technologies in making and delivering. Digital McKinsey. 2018:1-10.
- [16] Linton T, Vakili B. Coronavirus is proving we need more resilient supply chains. Harvard business review. 2020;5.
- [17] Craighead CW, Blackhurst J, Rungtusanatham MJ, Handfield RB. The severity of supply chain disruptions: design characteristics and mitigation capabilities. Decision sciences. 2007;38(1):131-56.
- [18] Ambulkar S, Blackhurst J, Grawe S. Firm's resilience to supply chain disruptions: Scale development and empirical examination. Journal of operations management. 2015;33:111-22.
- [19] Dubey R, Gunasekaran A, Childe SJ, Fosso Wamba S, Roubaud D, Foroqon C. Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. International Journal of Production Research. 2021;59(1):110-28.
- [20] Ketchen Jr DJ, Craighead CW. Toward a theory of supply chain entrepreneurial embeddedness in disrupted and normal states. Journal of Supply Chain Management. 2021;57(1):50-7.
- [21] Manhart P, Summers JK, Blackhurst J. A meta - analytic review of supply chain risk management: assessing buffering and bridging strategies and firm performance. Journal of Supply Chain Management. 2020;56(3):66-87.
- [22] Harland C. Discontinuous wefts: Weaving a more interconnected supply chain management tapestry. Journal of Supply Chain Management. 2021;57(1):27-40.
- [23] Burkov A. The hundred-page machine learning book: Andriy Burkov Canada; 2019.
- [24] Volvo Trucks' Collaboration with SAS Enhances Remote Diagnostics through Advanced Analytics and AI [press release]. Nort America: Volvogroup.com, 2018-10-25 2018.
- [25] Ni D, Xiao Z, Lim MK. A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics. 2020;11(7):1463-82.
- [26] Seyedan M, Mafakheri F. Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data. 2020;7(1):1-22.
- [27] Wang W, Rivera DE. Model predictive control for tactical decision-making in semiconductor manufacturing supply chain management. IEEE Transactions on Control Systems Technology. 2008;16(5):841-55.
- [28] Kelleher JD, Mac Namee B, D'arcy A. Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies: MIT press; 2020.