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INCREASE SUPPLY CHAIN RESILIENCE BY APPLYING EARLY WARNING SIGNALS WITHIN BIG-DATA ANALYSIS

Abstract

Purpose: The current environment of globally interconnected supply chains, the dynamics of changes and potential threats significantly reduce the time for a possible response. At the same time, there is a growing demand for information necessary to mitigate the consequences. To minimise the damage and increase the resilience of supply chains, it is necessary to identify sources of threats promptly, the extent of possible damage and the possibility of preventing or minimising their impact. The aim of the paper is to structure supply chain threats and search for appropriate datasets for prevention.

Methodology: The paper analyses the state-of-the-art through a comprehensive literature review and demonstrates secondary data about how free-access business data can be used as Early Warning Signals to forecast supply chain disruptive events, with a particular focus on international maritime transportation.

Results: It was confirmed that companies can access many open datasets, and collecting and aggregating these data can improve their preparedness for future disruptive events. As the most important issue, the authors defined the selection of proper datasets and interpreting results with foresight.

Conclusions: Identifying and analysing the relevant Early Warning Signals by companies to prevent supply chain disruptions are essential for keeping their supply chains sustainable and their resilience on a sufficient level. It was proved that general business indicators (PMI delivery time, container capacity, inflation rate, etc.) can help to signal the increasing possibility of maritime traffic problems in ports and container unavailability as usual supply chain disruption types in recent years. Therefore, the companies in the supply chains need to find, collect and analyse the appropriate data, which are, in some cases, free and available. However, it is a substantial task for data analysts to identify the most relevant data and work out the analytical methodology which can be applied as Early Warning Systems (EWS).

Keywords: Supply chain resilience, big-data analytics, high-impact low probability events, early warning signals

1. Introduction

Resilience is vital for designing and managing viable value-creation networks (Ivanov, 2021). In the global market, supply chains compete with each other, and their extent and complexity are a major concern from optimisation, design, efficiency or resilience points of view, even on the level of individual companies or the entire supply chain (Dujak, 2019). The ability of global supply chains to be resilient and flexible is indispensable since they face a wide range of threats, uncertainties, and sudden shifts in case the time and necessary resources for an adequate reaction are limited. Therefore, supply chains should be interpreted in a systems theory context. Supply chains today have to operate in a particularly turbulent environment. An important issue in such circumstances is the supply chain's ability to successfully maintain its operations while adapting to a dynamically changing environment.

The paper has the following structure: in the literature review part, the supply chain disruption approaches will be introduced, followed by the role of digital technologies in managing the supply chains, as well as big data analytics and how it can support supply chain management and what role early warning systems (EWS) can have in preventing disruptions. The following section will introduce the methodology. Since this is a theoretical paper, the framework we built is an example of using EWS to prevent disruptions in maritime transportation was identified as a key process in global supply chains. Finally, in the Conclusions, the findings and the relevance of the framework will be discussed as well as the limitations of the study.

2. Literature Review

To analyse the current state-of-the-art knowledge, professional publications from international databases of scientific publications, Web of Science (WoS) and Scopus were primarily used. At the same time, analyses of consulting companies and professional portals were reviewed. Open databases of the OECD and the World Bank were used as data sources.

2.1 Supply Chain Disruption Approaches

In the paper, the authors investigate how big data analytics can help supply chains become resilient to disruptive events. Many significant influencing factors affect the supply chain´s overall performance and long-term operational sustainability. A very appropriate categorisation of factors causing supply chain disruptions is found in Tang, Teo and Wei (Tang et al., 2008, pp. 206-208; Tulach & Foltin, 2020) and their three main categories:

- *Chain deviations:* a change in one or more control parameters, such as changes in costs, demand, or delivery times within the supply chain, without a change in the logistics chain's original structure;
- *Chain disruption:* a significant change in the supply chain structure due to the unavailability of some logistics nodes or their edges due to unexpected events caused by human or natural factors;
- *Disruption due to a disaster:* temporary irreversible closure of the supply network due to an unexpected, unforeseen disaster, which may cause total disruption of the functionality of logistics nodes and transport capabilities.

Threats might originate in various sources for supply chains. They can be irregular, catastrophic, or hybrid, emerging from hostile intentional or non-intentional activities, e.g., natural or disasters (Freier, 2008, p. vii). Supply chain disruption can be experienced inside or outside the supply chain (Narasimhan & Talluri, 2009). It can be intentional or unintentional (Foltin, 2011) and might concern supply chain flows like materials flow, information flow, knowledge flow, control and coordination flow (Neiger et al., 2009). Several research teams have also dealt with the consequences of catastrophic events (Knemaver et al., 2009) and the consequences of socioeconomic, political, man-made and natural disasters (Singh & Singh, 2019).

At the same time, the supply chains are exposed to disruptions, and usually, at some point, a warning about potential or upcoming problems is needed (Vries et al., 2021). The usual way of dealing with the need to predict potential disruptions of supply chains is to involve a group of experts to continuously evaluate changes in supply chains and the conditions of their operations (Jalowiec, 2020). The team of experts constantly monitors and evaluates these changes. In case of a threat of disruption or change in the chain's functionality, they give appropriate recommendations. The advantage of this approach is the high professional level of advice. However, their preparation is lengthy; it requires endless meetings and discussions with experts, so this method is also expensive.

The complexity of supply chains indicates that their management necessitates complex technological applications. Data about the material flows, data quality requirements and the need for information sharing between all logistics nodes become the obligatory requirement for value creation and supply chains' long-term operational sustainability. The decision-making process of planning and managing the supply chains/ networks also requires overall analytical support (Diop et al., 2021). Next to identifying risks threatening supply chains, managing such risks in global supply chains is also a hot topic. Its process is (1) identifying risk sources, (2) defining the circumstances under which such risks can occur, (3) estimating the potential consequences, and (4) providing possible routes to mitigating and handling these consequences (Tang et al., 2008, p. 210). Digitalisation might offer plenty of possibilities to support these activities.

The number of individual supply chain elements and their interconnections create a complex system which might also carry an inherent risk (Vlkovský, 2019). Therefore, it is substantial to identify the supply chain´s overall capabilities to define threats and sources of disruption, with the potential to improve resilience and long-term operational sustainability. Furthermore, the identification and recognition of unexpected events is a precondition for the possibility of managing the supply chain resiliently.

2.2 Role of Big Data in Supply Chain Management

Due to the overall complexity of the supply chains and the whole set of influencing interconnected factors, digitalisation can help to monitor the supply chain environment, create transparency and optimise processes (Ivanov et al., 2019; Bahrami & Shokouhyar, 2021; Modgil et al., 2021). These can contribute to a better understanding of the behaviour of individual entities within the supply chains.

Tseng et al. (2021) and Diófási-Kovács (2021) state that sustainable supply chain operations can be facilitated by the digital support of labour and manufacturing processes, diverse digital platforms, and extending digital communication. Core digital technologies like the Internet of Things (IoT) make the collection and exchange of large-scale data and the transmission of processing systems possible (Birkel & Hartmann, 2020). Additive technologies like 3D printing enable shorter lead times and manufacturing flexibility, increase product customisation, and reduce inventory (Ivanov et al., 2019). High levels of digital supply chain integration also can improve companies' financial performance and positively impact sustainability (Tseng et al., 2021; Negri et al., 2021). Digital technologies might impact supply chain risk management positively in numerous ways. The next chapter focuses specifically on Big Data from among all digital technologies. Big Data is created in multiple organisational processes in high volume, with high velocity and in a wide variety, which exceeds the capabilities of traditional data processing systems (Wang et al., 2016). The most significant impact of digitalisation is the possibility to capture, share, and process it. Data on its own is not worth much, and systems are needed that can process it. It will be explored how Big Data Analytics, as an important feature of digitalisation, can support the maintenance of supply chain security. The paper aims to present and propose the construction of a system to anticipate unexpected adverse events and thereby improve the resilience of supply chains.

2.3 Role of Big Data and Early Warning Systems in Preventing Supply Chain Disruptions

There are many forms of digital technologies in the supply chain that can help increase communication, collaboration, and the efficiency of information sharing. The widespread use of platforms raises agility, reliability, and efficiency while managing risks (Tseng et al., 2021). Big Data Analytics includes technologies, skills, and practices to structure and process data and provide helpful information for decision-makers.

Identifying risks threatening the supply chain is crucial when estimating the likelihood of disruptive events and possible consequences (Rehak, 2016). The management also has to assess the consequences, their magnitude, nature, complexity, and connectivity; all have to be studied in preparation for the possible occurrence. The volatility and time-related factors of threats should also be considered, as well as the effectiveness of the existing control mechanisms.

The paper focuses on how Big Data Analytics (BDA) can support these processes, what kind of data and from what sources should be collected and processed as Early Warning Signals to gain helpful information in preventing risks and helping supply chains to become resilient.

2.4 Use of Early Warning Systems

Scholars have already started to deal with how to use early warning systems in the supply chain. There are several case studies in the food industry on how EWS can help to predict quantity and quality problems (Li et al., 2010; Beulens et al., 2006) and identify the extent of risks (Xu et al., 2010). EWS can also be helpful in the fashion industry in predicting a range of risks – information, demand, supply, and environmental (Sumei, 2010) – and is also used in preventing customer loss (Lo & Hong, 2012). Customer churn detection is crucial in the banking and insurance sectors (Er Kara et al., 2018). Genc et al. (2014) studied an EWS to assess risks threatening production control, and Jahns et al. (2006) consider it a suitable tool for anticipating unexpected events in supply management.

Although examples can be found in the literature for EWS application for specific problems in the supply chain, the supply chain-level prediction and systematic analysis of disruptive events are not addressed yet. This study aims to fill this gap and provide a framework for using free access data as Early Warning Signals to prevent disruptive events in the maritime transportation process of global supply chains.

2.5 Role of EWS in Preventing Supply Chain Disruptions

Developing the analytical capabilities of supply chains and placing a strong emphasis on ensuring that they have the knowledge and decision-making capacity to deal with difficult situations allow them to operate resiliently (Modgil et al., 2021). However, the availability of large amounts of data tends to make the decision-makers' job difficult nowadays. Therefore, there is a strong need for building BDA systems capable of filtering, structuring, and analysing data in large volumes, variety, and from various sources (Demeter et al., 2021). Wamba et al. (2017) indicated that infrastructure, management skills, and staff expertise are needed to use BDA to the correct standard.

According to the limited case studies, Ford (Simchi-Levi et al., 2014) and IBM (Lu et al., 2015) use various quantitative modelling approaches to predict disruptive events threatening their supply chains. However, unexpected events significantly impact supply chain functionality – such as an earthquake or terrorist act – but are impossible to build accurate forecasting systems (Fattahi & Govindan, 2020). BDA can support the resilience of supply chains in numerous ways. According to Papadopoulos et al. (2017), big data has great potential for finding appropriate recovery strategies and for supply network management. Bahrami and Shokouhyar (2021) consider the most outstanding achievement of BDA the fact that it provides a deep insight into understanding the changes of the business and market environment, which allows companies to prepare for disruptions.

After reviewing the literature, it was found that although there are isolated examples of Big Data used in Early Warning Systems (EWS) in the supply chain, their prevalence and theoretical development are far from complete.

3. Research Aims and Methodology

The possible supply chain disruptions represent threats to the overall capabilities of the long-term sustainability of business continuity. As seen from the literature review, the range of threats to supply chains is very wide and it is not possible to address them in the same way. To this end, the analysis is narrowed down to the transportation process, a critical supply chain process that spans the entire supply chain from upstream to downstream. At the same time, the time horizon is crucial. The shorter the time horizon, the more accurate the possibility of prediction can be. On the contrary, in a longer time horizon, the probability of predicting potential threats and disruption of distribution chains is significantly lower.

In the era of global supply chains, transportation is particularly important, with maritime transport being the main performer of the flow of goods between global regions. Consequently, the success of this process is a key determinant of supply chain performance. It is therefore addressed in detail in this paper.

The study will focus on the type of intentional disruptions that poses a particular threat to the international maritime flow of goods and will further examine what data sets are available to predict the likely impacts when this type of contingency occurs and what indicators can be used to infer the extent of the impacts when operating the supply chain.

3.1 Research Goal

Based on the identified research gap, the primary effort was focused on identifying the suitable data sources and their interconnections, as well as the available BDA applications and their potential use as advanced prediction tools for possible supply chain disruptions. The focal question is *how supply chains can prepare for unexpected adverse events and take advantage of the opportunities offered by digitalisation to anticipate events that threaten them.*

The study approaches the subject primarily from a theoretical point of view, and an EWS will be proposed for supply chain disruptions. The research questions are the following: in case of a specific risk type – e.g., intentional but non-sudden threats – what kind of (big) data is needed, and what kind of free access data is available for use as an EWS to predict the possible occurrence of a supply chain disruption in the global maritime transportation process. The goals of the presented research are:

1) How can big data be used to predict disruption in the transportation process of supply chains?
2) How can it be used to anticipate events and support preparedness?

3.2 Data

When we started to analyse the research question, we faced the problem that even though there are many information sources, there is a lack of structured data which can be used to predict potential supply chain disruptions and be used as an Early Warning Signal for early identification of these threats. The lack of suitable data led the authors to the need to identify the main factors influencing the core tasks of supply chain management and the key aspects and factors influencing the performance of core supply chain processes.

A substantial question is how we can measure the performance of the supply chain processes, taking into account the uncertainty in their conditions and environment, and how to identify the possible sources of changes in advance (through the Early Warning Signals) to be able to identify the sources of potential disruptions and their probability.

Similar to critical success factors (Parmenter, 2015) and the proposed Key Result Indicators (KRIs), Result Indicators (RIs), Performance Indicators (PIs), and Key Performance Indicators (KPIs), the overall performance and effectivity of supply chain management can be assessed, based on previous results (past), results in real or almost-real time (present), with the possibility to forecast the future.

To find appropriate data sources to forecast disruptive events for maritime transportation in global supply chains, the authors overviewed the biggest economic shocks of the last decades having huge effects on supply chain operations, such as the recession in 2001-2002, the financial crisis in 2009, the Hanjin Shg bankruptcy in 2016, and the Covid-19 pandemic (Table 1). Based on the identified big shocks, keywords were defined that can describe that specific shock. These search words were applied in a bibliometric analysis in the Web of Science (WoS) and Scopus databases to catch their effects on supply chains. All in all, the keywords of the big economic downturns of past decades and their supply chain effects serve as the basis to define the appropriate Early Warning Signals for future intentional but non-sudden supply chain disruptions.

3.3 Methodological Approach

Since this study is theoretical, the methodology is a proposal for constructing an EWS framework. As discussed earlier, a large amount of data is available, much of which is freely available. However, deciding which data to select and from which source to predict a disruptive event is not always easy.

The authors have identified a research gap through the literature review and, by using publicly available data as an example, developed an analytical framework for predicting a specific supply chain disruptive event which currently poses the greatest threat to maritime freight transport, namely port congestion and container shortages. To this end, an example is presented of how and what data should be collected and what signs indicate that the emergency mentioned above is about to occur. For this purpose, past data from previous crises and the patterns observed in those crises are examined.

3.4 Research Limitations

The presented research primarily focuses on the theoretical background and system analysis. Due to the lack of appropriate data, the individual research steps come from the mind-maps experiments. This approach could be mainly subjective, with the general effort of objectification. This objectification could be considered a certain limitation of the research results.

The presented research is mainly theoretically focused on identifying possible interconnections between data availability, BDA, and EWS. At the same time, due to the lack of Big Data, there are certain research limitations because of using the theoretical mind-maps experiments, which from their purpose, bring subjective considerations, which were objectified in discussion with experts. For this reason, this objectification of the mind-maps experiments could be considered the main limitation of research results, but it also brings new possible points of view.

The research is focused on intentional threats that can be at least partially predicted. In the case of natural disasters, the possibility of predictability is very limited in terms of the time and place where they will happen and the extent of the impacts and affected actors. For this reason, the research is focused only on intentional sources of potential disruption of supply chains (Srinivasa, 2022).

4. Analysis and Results

Supply chain risk management has several inevitable steps. Its process is (1) identifying risk sources, (2) defining the circumstances under which such risks can occur, (3) estimating the potential consequences, and (4) providing possible routes to mitigating and handling these consequences (Tang et al., 2008, p. 210).

Signs or metrics are needed to measure the supply chains' performance to notice deviations from the normal supply chain operations. Planning and controlling the supply chain effectivity is usually possible through previously defined KPIs. Within the preliminary analytical part of the planning process, keywords can be sources of possible indices such as Early Warning Signs. From a macro point of view, it is hard to narrow managerial decision-making to only a few indicators or KPIs regarding the supply chain. For this reason, it is necessary to look at its main parts when optimising these and identify suitable analytical approaches next to the supply chain's system approach. The selected illustrative area in this paper is transportation. In this process of supply chains, it is possible to identify visible metrics for monitoring resilience and early warning signs by using BDA. The parameters for the transportation process of the supply chain are based on cross-sectorial and sectoral criteria. For this reason, the analytical framework covers the following:

(1) basic transport parameters, i.e., intensity, density, and permeability,

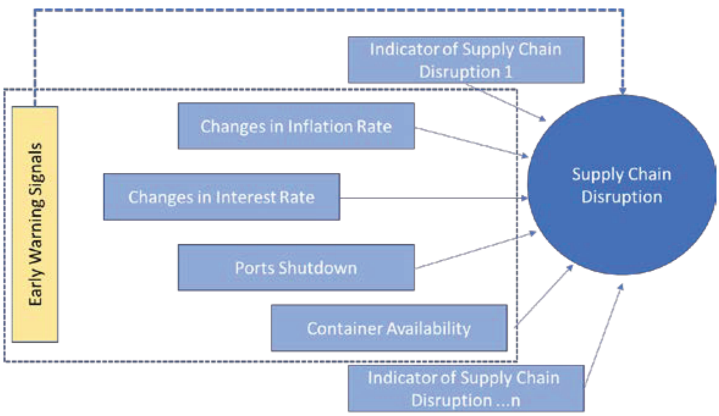
(2) parameters of the physical infrastructure (i.e., parts of tunnels, bridges, bridging, the height of bridges...), and especially the difficulty of possible restoration (costs and duration of restoration to the original parameters), the costs of detouring the designated object or the cultural and historical uniqueness of the object,

(3) transport services, which can be person or freight. In the case of one-person transport, the service is the transport of one person over a distance of km and is calculated as the product of the transport performance (i.e., the distance travelled by the given means of transport) and the number of transported persons [pkm]; for freight transport, transport performance represents the transport of one ton of goods per km,

(4) transport structure indicators, especially throughput and intensity.

Based on the parameters mentioned above, it is advisable, as a next step, to identify suitable examples of information sources that can be used as EWS for preservation or increasing the resilience of supply chains (Figure 1). Due to a large number of information sources, it is necessary to use the Big Data approach to find and compile a suitable data source and subsequently identify search algorithms and keywords.

Figure 1 Logic of the research process: Finding the right Early Warning Signals

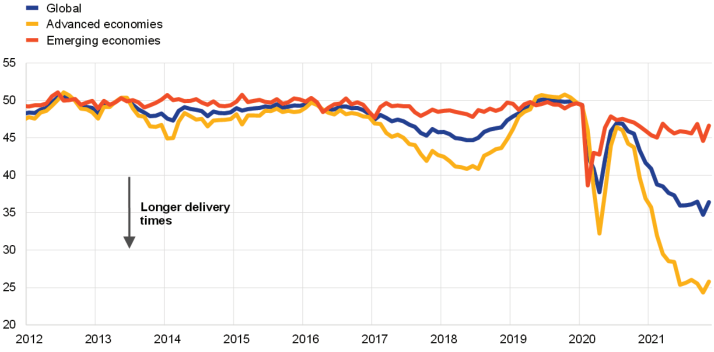


Source: Authors

4.1 Possible Identification of Supply Chain Disruption Proxies

One of the indicators most commonly used as a proxy for such strains is the global Purchasing Managers Index suppliers' delivery times (from now on referred to as the "PMI SDT"), which quantifies developments in the time required for the delivery of inputs to firms. A key advantage of the PMI SDT is that it can capture capacity constraints of a different nature (e.g. intermediate goods shortages, transportation delays or labour supply shortages) (Figure 2), making it an all-encompassing indicator of strains in global production networks (Attinasi et al., 2021).

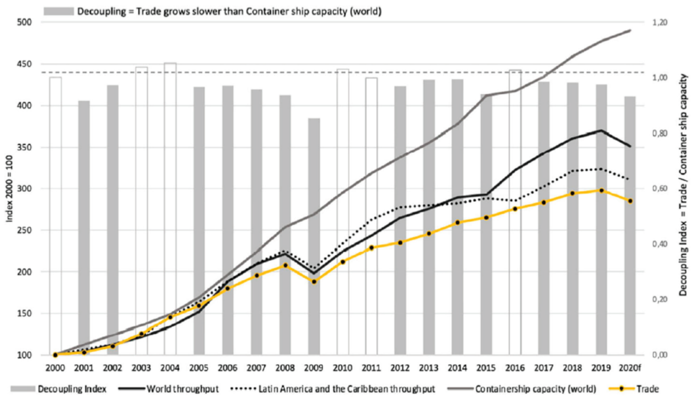
Figure 2 Suppliers' delivery times a) PMI SDT across regions (diffusion indices)



Source: Attinasi et al. (2021)

Key indicators in the transportation sector could be ship capacities and container availability. At the same time, shortages in ship and container capacity result from port congestion tying up the supply of ships, meaning that more ships are required to serve the same amount of demand (World Bank, 2021). Indeed, the presence of ships waiting to berth at ports suggests that the quantity of ships is not a binding constraint. Similarly, many experts, such as Drewry's John Fossey, note that overall container supply remains adequate to serve existing demand. Still, there is a mismatch between where containers are needed and where they are, and port congestion makes reallocation more difficult (Miller, 2021). The evolution of the trade and container ship availabilities is presented in Figure 3.

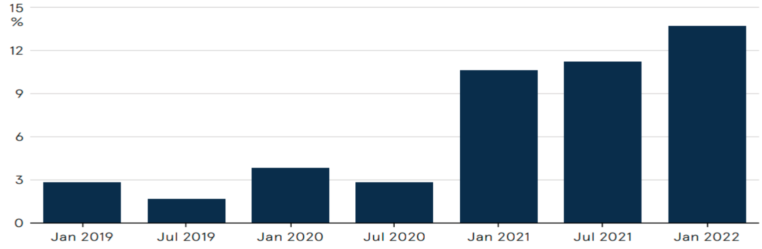
Figure 3 Maritime shipping capacity has generally grown faster than volumes



Source: World Bank (2021)

Maritime transport is a key indicator of changes in international trade. Changes in the availability of shipping capacity indicate subsequent changes. Figure 3 shows the effects of significant security changes, e.g. in connection with the increase in security measures due to the terrorist attacks on 11 September 2001, with their gradual onset in 2002. These years, international trade grew more slowly than the availability of free container capacities by ship. It was similar between 2005 and 2009 due to the global economic crisis. Military operations in the Persian Gulf and Afghanistan also occurred during this period. It was similar from 2012 to 2015 and grew from 2017 to 2019. The end of 2019 is the beginning of the Covid-19 pandemic, which is also visible on the international trade level and overall transportation capabilities. The important effect was the limited throughput of the international ports due to anti-Covid-19 restrictions. An example of container capacity lost due to port congestions and vessel delays is presented in Fig. 4.

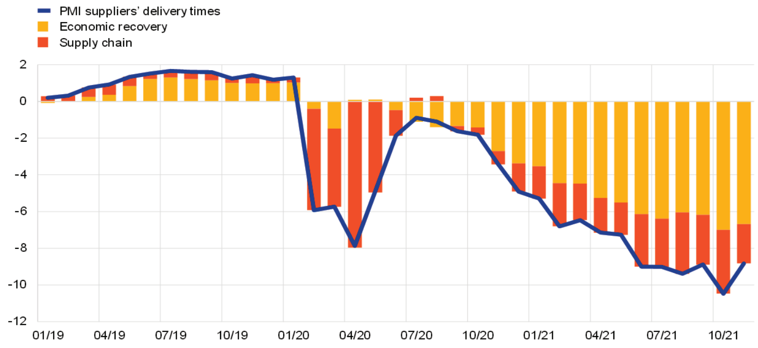
Figure 4 Share of the Global Container Fleet Capacity Lost due to Port Congestions and Vessel Delays [in %]



Source: Weinberg (2022)

However, the significant changes in available capacities can be challenging to predict in the longer term. So there remains the possibility of critical factor predictions focused on changes in trends in the availability of transport capacities and transport infrastructure. From a predictive point of view, the PMI, an indicator of the prevailing direction of economic trends in the manufacturing and service sectors, can be considered more appropriate. It consists of a diffusion index that summarises whether market conditions are increasing, staying at the same level, or decreasing from the perspective of purchasing managers. The PMI index provides information on current and future business conditions (Krúpa, 2022). The decomposition of PMI suppliers' delivery times is highlighted in Figure 5.

Figure 5 A model decomposition of PMI suppliers' delivery times (deviations from the mean; percentage point contributions)



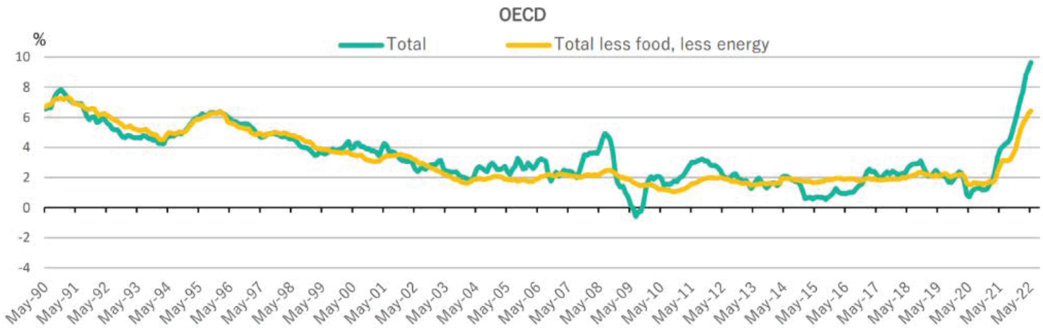
Source: World Bank (2021)

Supply chain disruptions have a negative impact on global industrial production and trade and a positive impact on inflation. Figure 5 also shows the interconnectedness of supply chain capabilities and the potential for economic recovery. There is also a visible interconnection and a possible explanation of the main shocks and consequences for supply chain performance.

4.2 Identification of the disruptions

As a potential metric for identifying possible disruptions, the inflation trend (see Figure 6) and the inactive containership capacity (see Figure 7) were selected. According to the annual data, the bottoms and peaks follow inflation. Significant threats or disruptions happened in periods of inflation peaks, e.g., in 1996, 2000, 2005 and 2006, 2007 (end of the year), 2011, and 2018 – and there were bottoms in inflation in 2009 and from 2014 to 2015. These inflation trends (Figure 6) present the interconnection with container capacity availability and offers a possible explanation of the main shocks and consequences for supply chain performance.

Figure 6 Inflation since the 1990s: All items and all items excluding food and energy OECD (CPI), year-on-year inflation rate

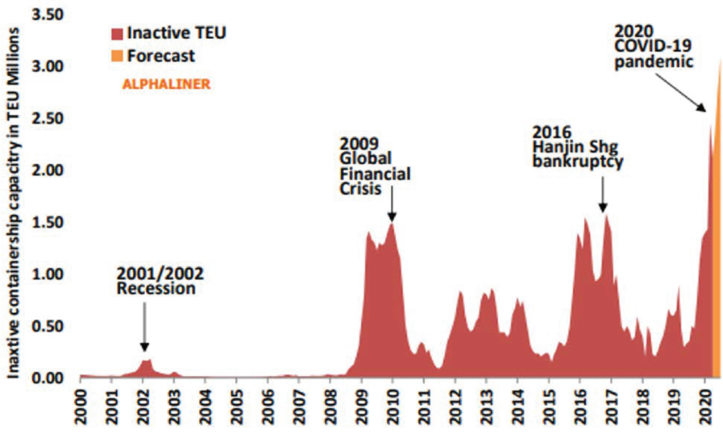


Source: OECD (2022)

4.3 Approach Verification through Data Sets

The World Bank Analysis offers good examples of the sources of possible supply chain disruptions. However, it is necessary to identify suitable keywords, or sets of keywords, which could be helpful when searching database sources for disruption forecasting. In the currently proposed theoretical framework, the applied keywords were selected based on the frequency of keywords in the articles in the WoS/ Scopus databases. In searching words sequence, the four threats were used, mentioned in Figure 7, and "supply chain" was added as the fifth keyword.

Figure 7 Inactive containership capacity (2000-2020(F))



Source: World Bank (2021)

As the first example, the keywords “recession” and “supply chain” were analysed, sorting articles by frequency of citations. The most quoted articles found with this method also list the keywords “financial risk” and “world economy”. It is possible to use more keywords, but only the first two were selected for research purposes. For the second search, “supply chain” and “global financial crisis” were used, and for the third, “supply chain” and” bankruptcy”. Finally, “supply chain” and “Covid-19” were used for the fourth search.

Table 1 Examples of BDA keywords and data sources

threat	period	possible additional keywords	possible source of data	reasoning
economic recession	2001/2002	- financial risk - world economy	- The World Bank – Economy[1]	- set of economic indicators
global financial crisis	2009	- supply chain resilience - supply chain vulnerability	- FM Global Resilience Index[2]	- 15 key drivers of resilience
Hanjin Shg bankruptcy	2016	- international business - risk management	- World Bank – Statistical Performance Indicators (SPI)[3]	- assessment of global performance
Covid-19	2020	- transportation services - exports of goods and services	- World Bank – Transport Services[4]	- level of transportation capabilities

Notes:

1) The World Bank – Economy, set of indicators (https://datatopics.worldbank.org/world-development-indicators/themes/economy.html)

2) FM Global Resilience Index – set of indicators (https://www.fmglobal.com/research-and-resources/tools-and-resources/resilienceindex/explore-the-data/?)

3) The World Bank – Statistical Performance Indicators (SPI) (https://www.worldbank.org/en/programs/statistical-performance-indicators)

4) The World Bank – Transportation (https://data.worldbank.org/indicator/BX.GSR.TRAN.ZS)

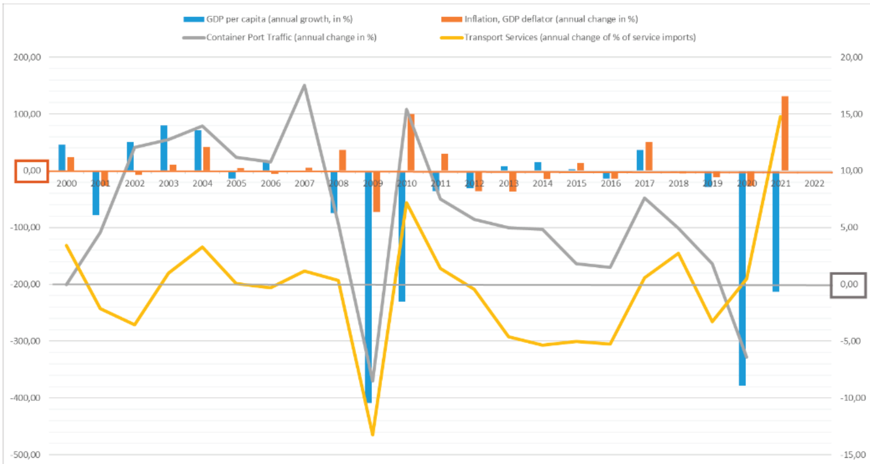
Source: Authors

From all identified sources, the economic indicators were found as the most important EWSs of the intentional but non-sudden threats endangering the supply chain with disruptions, which have predictable potential. Due to the nature of possible disruption to the supply chain functionality, uncertainty in the chain can manifest in three basic forms: internal chain deviations, chain disruptions, and disruptions due to a disaster (Tang et al., 2008, p. 206). The following selected macroeconomic and supply chains indicators were selected as EWS (World Bank, 2022):

- GDP per capita growth (annual %), as an indicator of the annual percentage growth rate of GDP per capita based on constant local currency;
- Inflation, GDP deflator (annual %), as an indicator measured by the annual growth rate of the GDP implicit deflator, which shows the rate of price change in the economy as a whole; GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency;
- Container Port Traffic (TEU: 20-feet equivalent units), as an indicator of measures the flow of containers from land to sea transport modes, and vice versa, in twenty-foot equivalent units (TEUs), a standard-size container;
- Transport Services (% of service imports), as an indicator of transport services performed by the residents of an economy for those of another, involving the carriage of passengers, the movement of goods (freight), rental of carriers with crew, and related support and auxiliary services.

The trendiness and interconnection of world economic and supply chain indicators are shown in Figure 8. The individual indicators were adjusted to a year-on-year percentage change to monitor correlating trends. This adjustment makes it possible to capture the change in trend and compare it with the changing trends of other indicators. To capture changes in trends in the selected variables, two basic levels (value 0) were set in the graph: on the left axis of the chart for column variables, i.e. world GDP per capita and world inflation (as a GDP deflator). In the right axis of the graph, the basic level (value 0) is set for the global indicators like Container Port Traffic and Transport Services. By interlacing the data in one chart, it is subsequently possible to identify the interconnectedness of the trends of annual changes.

Figure 8 World macroeconomic and supply chain indicators – annual change [%], years 2000-2021



Source: Modified from World Bank Data (2022)

Following the identified critical events disrupting the availability of container capacities (Figure 7) and connecting them with the selected indicators suitable for BDA (Table 1), in Figure 8 it is possible to identify predictive potential and make the following statements on the global level:

- In 2001-2002, when there was an economic recession, the economy's performance expressed in GDP per capita was the lowest in 2001, and in the following year, there was positive growth again. An increase in Container Port Traffic accompanied this change. In these two years, however, there was still a year-on-year decline in Transport Services, which began to increase again only in the middle of 2002 and reached its peak only in 2004. Also, Inflation (GDP deflator) reacted with a delay in the year-on-year comparison and gradually began to increase only from 2003.
- The global financial crisis in 2009 caused a significant decline in the economy's performance, expressed in the year-on-year change in GDP per capita. However, the year-on-year change in Inflation was not that significant, again with a delay of approximately one year, as was the case with the economic recession in 2001-2002. In the case of Transport Services, there was a significant year-on-year drop in the services provided, which was also matched by the drop in Container Port Traffic. For both indicators, however, there was a significant increase in the year-on-year comparison and the year-on-year trend. Container Port Traffic is pointed to as the pro-growth indicator of changes in economic performance.
- In the case of Hanjin Shg bankruptcy, a slight drop in economic performance and a correlating drop in inflation can be identified. Conversely, in the area of supply chain efficiency, there was a significant increase in the year-on-year trend change for Container Port Traffic and Transport Services.

- Regarding the effects of the Covid-19 pandemic, there was a fundamental drop in economic performance during 2020. This drop deepened even further in 2021, also reflected in a significant year-on-year change in inflation. In the case of Container Port Traffic, there was a year-on-year drop, but the level of Transport Services reached its 20-year high.

According to the above findings, authors identified a predictive potential based on BDA and EWS keywords:

- The events of the economic recession in 2001-2002 resulted in the possibility of predicting the development of GDP per capita and partially also Inflation according to the change in the Container Port Traffic trend.
- In the case of the global financial crisis in 2009, it is possible to identify a significant change in the Container Port Traffic trend already in 2008, i.e. before the financial crisis reached its maximum. The year-on-year change in trend is also visible on the Transport Services indicator, which reached an almost doubled level when economic growth resumed, representing a significant increase in the capacities of the global supply chain.
- The global effects of Hanjin Shg bankruptcy on the global economic performance and inflation indicators cannot be confirmed due to the chosen macro view on the sustainability of supply chains.
- Regarding the effects of the Covid-19 pandemic, it was possible to identify the year-on-year changes in Transport Services as a suitable indicator predicting changes in economic performance, which, assuming ceteris paribus, would occur in the second half of 2022.

5. Conclusions

It is hard to predict the disruptive effects of High Impact Low Probability (HILP) events on the supply chains because of the unpredictability of these events. Similarly, it is hard to predict big natural disasters since these threats are accidental. Only several high-frequency natural disruptions, e.g., annual floods, can be predicted, but forecasting events like flash floods is impossible.

The importance of the time horizon for the prediction of potential disruptions is highlighted in this paper. Based on the relevant information, it is possible to predict short time disruptions and their possible consequences. In long-term prediction, the probability is significantly decreasing with time.

For the maritime transportation process in the global supply chain, the expected performance can be measured by several KPIs. If there is any significant deviation in these KPIs when an intentional and non-sudden event occurs in the environment or the market the supply chain operates in, Early Warning Signals can be observed; thus, the disruption and its effects can be predicted. To carry this out, supply chains and companies must define and continuously measure transportation KPIs throughout the chain and use BDA systems that assess economic data – suggested as examples in Table 1 – that can forecast specific types of economic downturns threatening the supply chain.

We proved that general business indicators (PMI delivery time, container capacity, inflation rate, etc.) can indicate the increasing possibility of maritime traffic problems in ports and container unavailability as usual supply chain disruption type of recent years. The companies in the supply chains need to find, collect and analyse the appropriate data, which are, in some cases, free and available. However, it is a substantial task of data analysts to identify the most relevant data and work out the analytical methodology which can be applied as Early Warning Systems (EWS).

As a part of the research carried out, it was confirmed that through identified EWS, it is possible to predict some changes in transportation capabilities and infrastructures. These indicators and indices will need further testing in real applications, using real data development and then checking the probabilities of successful predictions. It is necessary to verify further the interconnectedness of the identified trends of the selected indicators on a longer time series and specific events. Further research will therefore aim to confirm this connection between indicators and events on national level. The trends and early warning signals should also be tested on the country level to identify direct links to specific events and national-level indicators to call the attention of country/ies to the threats they need to deal with.

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