Food supply network disruption and mitigation: an integrated perspective of traceability technology and network structure

Lili Wang¹ · Bin Hu¹ · Yihang Feng¹ · Yanting Duan¹ · Wuyi Zhang²

Accepted: 17 August 2022 / Published online: 1 October 2022
© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2022

Abstract
The 2019 coronavirus disease (COVID-19) epidemic has caused serious disruptions in food supply networks. Based on the case of the remerging epidemic in China, this paper aims to investigate food supply network disruption and its mitigation from technical and structural perspectives. To solve the optimal policy choice problem that how to improve mitigation capability of food supply networks by using traceability technology and adjusting network structure, the occurrence mechanism of food supply network disruptions is revealed through a case study of the remerging COVID-19 outbreak in Beijing’s Xinfadi market. Five typical traceability solutions are proposed to mitigate network disruptions and their technical attributes are analyzed to establish disruption mitigation models. The structure of food supply networks is also controlled to mitigate disruptions. The structural attributes of three fundamental networks are extracted to adjust the network connections pattern in disruption mitigation models. Next, simulation experiments involving the disruption mitigation models are carried out to explore the independent and joint effects of traceability technology and network structure on mitigation capability. The findings suggest that accuracy makes a more positive effect on the mitigation capability of food supply networks than timeliness due to the various technical compositions behind them; the difference between these effects determines the choice decision of supply networks on traceability solution types. Likewise, betweenness centralization makes a positive effect but degree centralization makes a negative effect on mitigation capability because intermediary firms and focal firms in food supply networks have different behavior characteristics; these effects are both regulated by supply network types and exhibit different sensitivities. As for the joint effect of technical and structural attributes on mitigation capability, the joint effect of accuracy and betweenness centralization is bigger than the independent effects but smaller than their sum; the joint effect of timeliness and betweenness centralization depends on networks type; while the positive effect of accuracy or timeliness on mitigation capability is greater than the negative effect of degree centralization; these joint...
effects are caused by the complicated interactive effects between technical composition and behaviors of intermediary firms or focal firms. These findings contribute to disruption management and decision-making theories and practices.

**Keywords** Food supply network · Supply disruption · Traceability · Network structure · Covid-19

## 1 Introduction

Since 2020, the COVID-19 has spread across China and beyond. The epidemic (the outbreak of the COVID-19) has disrupted local and global supply chains, leading to serious economic and social losses (Wu et al. 2020). In the COVID-19 Post-Pandemic era, the food industry found itself facing the gravest crisis as the COVID-19 frequently contaminated food products. For example, the reoccurrence of coronavirus disease in Chinese cities (such as Beijing, Dalian, and Tianjin) was proved largely related to imported frozen food or food wholesale markets (Zhou and Shi 2021). To control the disease, the relevant food suppliers were inspected, which caused an increasing number of food supply disruptions and profound social and economic impacts. The unpredicted condition has attracted high levels of academic and industrial attention to food supply disruption management.

Food contamination is the primary cause of disruptions. Because food supply networks are fast-moving supply systems, if contamination occurs, the widespread of contaminated products in a short time is highly likely. Before food contamination is identified, contaminated foods may have been distributed throughout the supply network (Chebolu-Subramanian and Gaukler 2015), ultimately resulting in large-scale supply disruption. Furthermore, food supply networks tend to have complicated structures because of the high level of competition in food markets. This characteristic can make the accurate recognition of contamination sources especially challenging. In a word, the food products are easily contaminated by the COVID-19, and it is hard to detect food contamination in real-time or determine the contamination source accurately due to the unique properties of food products, which causes the frequent occurrence of disruptions in food supply networks.

The traditional strategies to mitigate supply disruptions are constructed based on the robustness and resilience of supply chains (El Baz and Ruel 2020). To hence the robustness, a redundant method (e.g., multi-sourcing procurement, back-up suppliers, and safety stock) is usually adopted by supply chains (Xu et al. 2020; Kumar et al. 2018). While resilience is usually promoted through flexibility, such as coordination of supply and demand, resource reorganization, and establishment of flexible production lines (Bugert and Lasch 2018; Mohammadzadeh and Zegordi 2016; Kumar et al. 2018). However, the old methods could hardly deal with disruption risks in food supply networks as they ignore the properties of food products (Mai et al. 2010).

Traceability technology is applied as a method to solve the above problem. Traceability technology differs from traditional strategies as it defends food supply...
networks against network disruptions via its technical attributes (Wen et al. 2018), such as providing the real-time status of food or supporting accurate identification of contamination sources to mitigate disruptions (Piramuthu et al. 2013). Generally, accuracy and timeliness are two crucial technical attributes of traceability technology, determining the ability of traceability technology to manage supply disruptions. The relationship between components of traceability technology and disruptions in food supply chains is the focus of current research.

What’s more, traceability technology is essentially an emerging network technology, whose technical attributes have an interactive relationship with network structure (Lu et al. 2019; Li et al. 2019). On the one hand, it is supposed that the application of intelligent traceability will affect the structure of supply networks. For example, the real-time remote inquiry system in logistics that works as an intelligent traceability system could reduce the non-standard operation of logistics back-end and simplify the terminal network structure (Li et al. 2019). On the other hand, the network structure also significantly affects the application of traceability technology. For example, Lu et al. (2019) demonstrated that both the network density and degree distribution of the food supply network affect the tracking ability of intelligent systems by implementing a series of simulation experiments. Besides, the structural attributes of supply networks also make a more profound effect on disruptions. Both the structural configuration and structural parameters can be adjusted to mitigate disruptions (El Baz and Ruel 2020). Therefore, network structure is an unavoidable topic if we want to explore the relationship between disruptions and traceability in the context of a supply network. However, the interaction between traceability technology and network structure and their joint effects on food supply network disruptions remain unclear. Thus, further studies are warranted.

Given the gaps in the existing literature, the present paper aims to investigate the disruptions mitigation from an integrated perspective of traceability technology and network structure. We study the disruptions mitigation capability of a food supply network and its changing tendency when the network adopts traceability technology and adjusts its network structure. The occurrence of food supply network disruptions is demonstrated in a case study of food supply network disruptions in the remerging COVID-19 outbreak. Next, a problem is proposed: how to affect disruptions mitigation capability of food supply networks by using traceability technology and adjusting network structure. To solve the problem, five typical traceability solutions are proposed to mitigate network disruptions and their technical attributes are analyzed to establish disruptions mitigation models. The structure of food supply networks is also controlled to mitigate disruptions. The structural attributes of three fundamental networks are extracted to adjust the network connections pattern in disruptions mitigation models. Thus, traceability technology and network structure are integrated into a unified framework. Mitigation capability is proposed to measure the ability of supply networks to withstand disruptions. In total, simulation experiments are carried out to explore the independent and joint effects of traceability technology and network structure on mitigation capability. The methodology of this paper is based on a real-life case-study with real industry data. The agent-based modeling and simulation are also used to establish models and carry out simulation experiments to solve the problem proposed. The objectives of this analysis are threefold.
First, it aims to show how the functions of traceability technology and the choice decision on traceability solutions influence network disruptions mitigation. Second, it aims to demonstrate how network types and their connections pattern can improve the disruptions mitigation capability of supply networks. Third, this paper also aims to provide direct insight into the joint effect of traceability technology and network structure and give advise on technical and structural policies in practice.

This research contributes to the literature in the following ways. At first, this study views the accuracy and timeliness as the new principles of disruption management and puts forward the new mitigation methods based on traceability technology, which breaks through the limitation that disruption management only centers around robustness and resilience. Second, a systematic analysis of traceability solutions is conducted in the food supply network setting, which integrates traceability technology and network structure into a unified framework. The framework breaks the trend that current researchers study traceability only from the technical perspective and enriches the theories in the two aspects. Third, the disruption mitigation models in this study are established on traceability solutions and their technical attributes, which characterizes how typical traceability solutions function during food supply disruptions. The models can help us have a profound understanding of traceability technology. At last, this study formulates the occurrence mechanism of food supply network disruptions through an actual case in the remerging epidemic of COVID-19, which enables the theories on disruptions to have a practical basis and the conclusions of this paper to be of greater practical significance.

The layout of this paper is as follows: The external applications, internal mechanisms, and solution evaluation of traceability technologies are examined in depth in Sect. 2. Methodology is introduced in Sect. 3. Section 4 presents the case study and defines the concept and occurrence mechanism of food supply network disruptions. Section 5 proposes the problem and develops a group of disruption mitigation models. Section 6 illustrates the fundamental structures of food supply networks in the disruption mitigation models. Section 7 carries out simulation experiments and Sect. 8 makes discussions on the main findings. Finally, further research are highlighted.

2 The overview of traceability technology

2.1 Applications of traceability technology in disruptions management

Traceability has become a growing concern and novel technologies are rapidly being developed to mitigate supply disruption. Many researchers have explored specific application scenarios of traceability in the event of supply disruption (Mai et al. 2010; Lu et al. 2019; Wattanakul et al. 2018; Zhang et al. 2009; MacKenzie and Apte 2017; Piramuthu et al. 2013; Dandage et al. 2017). The majority of these studies considered that supply disruption in food industries could be effectively influenced or managed by traceability. As discussed above, a common reason for food supply disruption is a delay in identifying food contamination. Due to this delay, the contamination can spread widely as food products or materials flow through the
supply chains (Chebolu-Subramanian and Gaukler 2015). Efficient operations in the food industry tend to exacerbate small failures into larger failures. Furthermore, food products are commonly transformed in terms of their physical shape or chemical properties by cooking, squeezing, splitting, mixing, or other processing procedures, which can further impede identification of the contamination source and correction of failed procedures (Storøy et al. 2013). These unique characteristics of the food industry necessitate the adoption of traceability to mitigate supply disruption.

2.2 Impact of traceability on food supply disruptions

The impact of traceability on food supply disruptions has also become a research focus. Mai et al. (2010) used a case study of fish products to illustrate how a traceability system could help reduce disruptions in fish supply chains. Wattanakul et al. (2018) formulated a conceptual framework based on a smart traceability system, which confirmed that the negative impact of disruptions on supply chains could be mitigated by real-time analysis and careful monitoring of disruptions. Zhang et al. (2009) compared the performance of a temperature-managed traceability system and a traditional system in frozen food chains by a system test and experimental evaluation. The temperature-managed traceability system proved itself to be a powerful tool for controlling disruption risks and reducing spoiled food by enabling constant monitoring and documenting the status of goods in the cold supply chain. Chongwatpol and Sharda (2013) proposed an RFID-based traceability approach to improve production scheduling. A simulation experiment comparing the performance of the RFID-based scheduling rule and the traditional scheduling rules demonstrated the real-time tracking ability of the former and its advantage over the latter. MacKenzie and Apte (2017) developed a mathematical model of disruption resulting from food contamination in fresh produce supply chains and then analyzed the relationship between traceability and food supply disruptions. The results indicated that traceability could accurately trace and report the derived information of the contaminated goods and share information about unaffected nodes in the supply chain, thus prompting correct actions and mitigating losses caused by disruptions. In conclusion, compared to traditional mitigation strategies for supply disruption management (such as redundancy, flexibility, or cooperation, as proposed by Mohammadzadeh and Zegordi 2016; Kumar et al. 2018), traceability offers better performance due to its advantages of real-time detection and accurate identification (Wen et al. 2018).

2.3 Typical traceability solutions and their evaluation criteria

The ability of traceability technologies to mitigate food supply disruptions is largely due to their accuracy and timeliness. Óskarsdóttir and Oddsson (2019) regarded these features as the two main indicators for evaluating traceability systems. For example, traceability technologies are divided into static traceability and dynamic traceability based on their ability to collect data and interact with information in real-time. Dynamic solutions offer better timeliness than static solutions and can be grouped according to the level of timeliness. By contrast, static solutions can be separated into barcode-based
solutions and RFID-based solutions according to their ability to report data accurately. The advantage of the former over the latter is to reduce human error and improve accuracy. Learning from the above studies, this paper puts forward five typical traceability solutions: the traditional solution, static solution, one-point dynamic solution, three-point dynamic solution, and five-point dynamic solution. These five solutions are introduced in greater detail in Sect. 5.

As a new method of managing supply disruptions, traceability systems including their external applications, internal mechanisms, and solution evaluation have been thoroughly investigated using various methods, such as case studies, mathematical models, and simulation experiments. Research from other fields like operations management and logistics management has proved that traceability is essentially a network technology and that a proper network structure can strengthen the impact of traceability (Skilton and Robinson 2009; Lu et al. 2019). However, the extant literature has taken a single perspective on the technical attributes when examining traceability and supply disruptions, neglecting the network attribute of traceability (Wattanakul et al. 2018; Zhang et al. 2009; MacKenzie and Apte 2017).

To fill this research gap, the present study tends to investigate the mitigation capability of food supply networks during network disruptions. For this purpose, we introduce a case of the food supply network disruption to demonstrate the occurrence mechanism of disruptions in the next section.

3 Methodology

Because this paper focuses on a network disruption problem concerning the random failures of entities in networks, the agent-based modeling simulation methodology for the given problem domain has earned an important role in academic research (Nair and Vidal 2011; Kim et al. 2015). In the 1990s, the case study was the most popular method for disruption management studies as disruption was regarded as a one-time and single-node failure problem (Chapman et al. 2002). Mathematical analysis has been another important method since scholars began to consider supply chain channels when exploring the disruption problem (Kumar et al. 2018). In comparison to the two prior related methods, simulation has advantages in the complex network setting. It can handle dynamic changes and behavior characteristics of entities in networks over time. This is unavoidable when this study considers disruption dynamic spread and entities’ autonomous selection in networks. The multi-agent simulation method is therefore selected in this paper.

For validation, simulation experiments are carried out in Matlab software. Three networks and their structural attributes are extracted from real food industries to support experimental implementation. The application of the multi-agent simulation method is thus illustrated in the experiments.
4 Case study on occurrence mechanism of food supply network disruptions

In this sector, a case of remerging COVID-19 outbreak is explored to illustrate the concept and occurrence mechanism of food network supply disruptions.

On June 11, 2020, the second outbreak of COVID-19 began in Beijing’s Xinfadi market. On June 12, it was discovered that the cold supply chain food (frozen salmon) in the Xinfadi market had been contaminated by COVID-19 (Wu et al. 2020). The epidemic contact tracing supported that the food contamination had occurred before it was discovered. Due to the time delay between contamination occurrence and discovery, the contaminated products had quickly spread to downstream entities of the supply chain, which caused the closure of the downstream suppliers on June 13 (Han et al. 2021). Furthermore, a great number of relevant upstream suppliers were also involved because of the epidemic origin analysis. Because the traceability technology applied in the market could not provide accurate identification of source contamination, more upstream suppliers were shut down than expected. For example, the important salmon in the Xinfadi market was purchased from the Jingshen seafood wholesale market. When contamination of COVID-19 was identified in the chopping board of important salmon in the Xinfadi market, the relevant supplier in the Jingshen seafood wholesale market was also closed to detect COVID-19 and search its source (Cui 2020). However, the salmon products have undergone a complete transformation of physic shape. The traceability systems in both Jingshen and Xinfadi markets were based on barcode technology. They could not record sourcing information of products accurately, especially when there exists products transformation. Thus, the number of closed suppliers in the Jingshen market further increased (Jia and Sun 2020). As a result, the food supply network of salmon products has experienced widespread disruptions for two months (from June 13 to August 15), during which the flow of goods was completely cut off.

During the epidemic, the Xinfadi market greatly adjusted its structure to cope with disruptions. There used to be a lot of underground and semi-underground transactions in the Xinfadi market before the epidemic of COVID-19. The network structure is rather complex because of the chaotic management. However, when the market was fully resumed on September 6, it strictly implemented the policy of “separation of wholesale and retail” and carried out modular management (Sun 2020). Wholesalers purchased products only from standardized planting farms and implemented the “point-to-point” replenishment (Sun 2020). The structure of the supply network thus achieves the transformation from a free-connected pattern to a modular pattern.

According to this case, the concept of food supply network disruption can be defined as a complete disruption of logistics flows in a food supply network that resulted from food contamination and large-scale closure of suppliers in the network.

The case study demonstrates that a food supply network disruption involves four interconnected processes, including contamination occurrence, contamination transmission, contamination discovery, and closure of entities. In general, the progress can be summarized as the occurrence mechanism of food supply disruptions.
Contamination occurrence is the first stage. Contamination initially occurs at a supplier or transportation between two suppliers in a food supply network. This supplier or transport segment is called the initial contamination point or contamination source.

The second stage is Contamination transmission. In practice, it is impossible to detect food contamination as soon as it occurs. Delay in the discovery of the contamination, as well as the fast and effective operations of food product networks, enables the fast spread of the contaminated products or materials in downstream suppliers.

The next stage is Contamination discovery. The contaminated products then are discovered at one of the downstream suppliers or transport segments, which is termed the terminal discovery point. The walk of the contaminated products flowing from the initial supplier to the terminal discovery point can be defined as the contamination path. Notably, the initial contamination point is located on the contamination path. The products are in normal condition until reaching the initial contamination point.

Closure of entities is the last stage. After the contamination was discovered, the next is to find the initial contamination point (contamination source) and to stop the operation of related entities. However, current traceability technologies usually cannot exactly determine the position of the initial contamination point. What can be obtained through current technologies is an area where the initial contamination point is probably located. The area is defined as the identification area of contamination (IAOC). Its actual scope depends on the technical attributes of the traceability solution applied. For example, an IAOC may be limited to a segment of contamination path by implementing a traceability solution with high-level accuracy and timeliness. But the traceability solution with low accuracy and bad timeliness cannot even recognize a clear contamination path, thus causing a wider IAOC. To prevent the spread of contamination, all entities in IAOC and transportation between them will be closed for inspection and rectification. Thus, food contamination results in large-scale disruption of suppliers or transportation and leads to a complete interruption of logistics flows, i.e., food supply network disruption.

The case also indicates that the key points leading to a larger-scale disruption are delay in detecting food contamination and imprecision in identifying contamination sources. Besides, the primary strategies for mitigating network disruptions focus on two points, namely improving traceability technology and optimizing network structure.

5 Problem description and model formulation

5.1 Mathematical problem description

Here, we study a food supply network and its mitigation capability during network disruptions caused by the epidemic of COVID-19. According to the above case study, we can describe the problem of food supply network disruptions in the context of complex networks.
Based on complex networks theory (Anzola et al. 2017), a food supply network is characterized as a digraph $SN = (N, A)$, $(N = \{n_1, n_2, \ldots n_i\}, A = \{a_1, a_2, \ldots a_j\})$ (illustrated as Fig. 1), where $N$ is the collection of the nodes and $A$ is the collection of the directed arcs in the network. The number of source and sink nodes is set as 1 to reflect the most basic food network. Also, the number of nodes is set to be 12 ($i = 12$) to guarantee a larger enough network scale. The related terms and their definitions to describe food supply network disruptions are illustrated in Table 1.

According to above case study, the flow of physical goods should be fluent and uninterrupted in the normal situation as the network is initially connected (shown as Fig. 2a). Then, contamination occurs at the initial contamination point ($op_i$). The contaminated products are assumed to be kept in the same batch during circulation, so downstream spread of contamination is stopped at the terminal discovery point denoted as ($tp_i$). The contamination path ($W_{ij}$) between the source node and the terminal discovery point needs to be identified. This identification as well as IAOC ($Z$) is determined by network structures, traceability solutions, and their performance when dealing with information of food product transformation. Disruption at the node or arc level is reflected by the removal of the node or arc (shown as Fig. 2b). All of the nodes and arcs in the IAOC are removed to reflect the closure of suppliers (shown as Fig. 2c). As a consequence of disruptions in nodes or arcs, two situations of supply network $SN$ will be discussed. One situation is that at least one walk between the source and sink still exists, which is called the non-occurrence of network disruption. While the other situation is that none of the walks exists in the supply network $SN$, which is defined as the occurrence of network disruption (Kim et al. 2015; Buchta et al. 2003).

This paper aims to investigate how a food supply network could improve its mitigation capacity by using traceability technology and adjusting network structure when it faces network disruptions. To achieve this research objective, we assumed that food supply network $SN$ could make two mitigation policies:

- Adopting traceability technology to change its mitigation capability (five typical traceability solutions and their technical attributes are provided, including the traditional solution, the static solution, the one-point dynamic solution, the three-point dynamic solution, and the five-point dynamic solution; accuracy ($A$) and timeliness ($T$) are seen as the technical attributes of these solutions).
- Adjusting network structure to change its mitigation capability (three unique networks and their structural attributes could be chosen, which are the block-diagonal network, the scale-free network, and the centralized network; betweenness centralization ($C_B$) and degree centralization ($C_D$) are set as the structural attributes of these networks).

Next, we establish the disruption mitigation models based on these mitigation policies to measure mitigation capability of supply networks during disruptions, evaluate the effects of traceability and structure on mitigation capability and solve the optimal policy choice problem.
Food supply network disruption and mitigation: an integrated...

Fig. 1 An example of definitions in supply network disruptions
5.2 Assumptions and parameters

The models in this study are developed based on the following assumptions:

1. The number of source and sink nodes is set as 1, reflecting the most basic food network.
2. The number of nodes is set to be 12 to guarantee a larger enough network scale.
3. The nodes in the network are labeled 1 through 12, with more upstream nodes having lower numbers.
4. It is assumed the contaminated products are kept in the same batch during circulation because many cases of the remerging epidemic of COVID-19 were discovered in small scale or single food batch.

| Symbol | Definition |
|--------|------------|
| SN     | A digraph that depicts a food supply network |
| N      | Collection of the nodes |
| A      | Collection of the directed arcs |
| n_i    | Nodes of food supply networks, representing supply entities (such as growers, processors, packagers, brokers, distributors, wholesalers, and retailers) with the index i |
| n_1    | The source node, representing the initial supplier of the food supply network |
| n_12   | The sink node, representing the terminal consumer of the food supply network |
| a_j    | Directed arcs of food supply networks, reflecting food goods or materials flows between entities. The direction of arcs represents the direction of flows |
| W      | A walk that is formed by alternately connected nodes and directed arcs, representing a path between source and sink nodes. For example, W = {n_1, a_1, n_2, a_3, n_4, a_10, n_9, a_16, n_12} in Fig. 1 |
| UP_n_i | The collection of the node n_i’s upstream suppliers in all levels |
| DN_n_i | The collection of the node n_i’s downstream suppliers in all levels |
| op_i   | The initial contamination point, where i is the index of the node. For example, op_5 in Fig. 1 |
| tp_i   | The terminal contamination point, where i is the index of the node. For example, tp_9 in Fig. 1 |
| W_ij   | A contamination path beginning from n_i and ending up with n_j. For example, W_19 = {n_1, a_1, n_2, a_11, n_9} in Fig. 1 |
| Tn_i   | The transforming node that is directly linked to n_i, where i is the index of the node, representing food manufacturers or processors directly obtaining raw materials from initial suppliers. For example, Tn_2, Tn_3 in Fig. 1 |
| Pn_i   | The pre-transforming node that is between a transforming node and n_i, where i is the index of the node, representing factories purchasing materials from the initial suppliers and providing pre-treated ingredients to the focal manufacturers or processors. For example, Pn_6 in Fig. 1 |
| Pn     | The collection of pre-transforming nodes |
| Z      | The identification area of contamination |
Fig. 2. An example of food supply network disruptions.
(5) There are no isolated nodes, reflecting the food supply network is a unified system.
(6) The food supply network is connected, implying there exists at least one walk between the source and sink nodes.
(7) Disruption at the node or arc level is reflected by removal of the node or arc.
(8) To exclude extremely simple and complex networks, betweenness centralization of supply networks ranges from 0.70 to 0.95, and degree centralization ranges from 0.02 to 0.60 according to the actual data.

Parameters in the models are summarized in Table 2.

5.3 Typical traceability solutions and disruption mitigation model formulation

Here, the technical attributes of typical traceability solutions are analyzed to develop a group of disruption mitigation models in the setting of complex food networks. The models represent the unique functions of typical solutions when facing food network disruptions.

5.3.1 Technical attributes of typical traceability solutions

Accuracy and timeliness are regarded as the technical attributes of typical traceability solutions.

Traditional traceability solutions are based on barcode technology, a basic data storage system attached to a final product and linked to product historical information (Chongwatpol and Sharda 2013). Low cost is an overwhelming advantage of this technology. However, the need for a line of sight and manual operation when reading data make traditional traceability solutions unsuited for quickly and accurately tracing detailed information about food transformation (Óskarsdóttir and Oddsson 2019). The historical information only after food transformation can be recorded, limiting flexibility and automation (Dandage et al. 2017). Furthermore, barcode systems cannot provide real-time information as they do not have sensing ability or communicating ability (Óskarsdóttir and Oddsson 2019). Due to these limitations, traditional traceability solutions have low accuracy and bad timeliness.

Static traceability solutions were initially proposed through applications of Internet of Things (IoT) systems (Ding et al. 2021). This solution type uses RFID

| Table 2 | Parameters in the models |
|---------|--------------------------|
| Symbol  | Parameters               |
| A       | The accuracy level of traceability solutions |
| T       | The timeliness level of traceability solutions |
| C       | Cost of traceability solutions |
| C_B     | Betweenness centralization of supply networks |
| C_D     | Degree centralization of supply networks |
technology, which attaches identification tags to products to store product origin information (Gautam et al., 2017). Unlike barcode technology, the information is read via radio frequency (Óskarsdóttir and Oddsson 2019), which relaxes the requirement for a light of sight and embeds RFID systems with the ability to automatically read and write many tags at a time. Automated scanning and batch processing help to quickly and accurately process large amounts of complicated information associated with food products’ sources and destinations, even when there is product transformation. The primary disadvantage of RFID technology is that tags are not able to communicate with the reader on time and lack detecting and sensing ability (Óskarsdóttir and Oddsson 2019). This prevents RFID technology from acquiring the exact location of the initial contamination point and providing timely warnings of disruption. In summary, static traceability solutions offer medium accuracy and bad timeliness.

**Dynamic traceability solutions**, also called gate-way traceability solutions, rely on an integration of RFID and wireless sensor networks (WSN) (Mejjaouli and Babiceanu 2015). A WSN is “an infrastructure that consists of sensing, computing, and communication capability” (Mejjaouli and Babiceanu 2015). The most common type of WSN-RFID architecture is an integration of RFID tags with sensors (Óskarsdóttir and Oddsson 2019), i.e., adding wireless sensors to RFID tags and providing these tags with the ability to transmit data to RFID-enabled checkpoints. The roles of the wireless sensors are to monitor food product quality, collect related status information (such as temperature, vibrations, humidity, or other product parameters), and then send this information to the RFID tags (Mejjaouli and Babiceanu 2015). The RFID tags store quality information obtained from the wireless sensors, as well as origin information for transported products. Several RFID-enabled checkpoints are deployed along the transportation path to read the information stored on the food products’ RFID tags (Mejjaouli and Babiceanu 2015). If any abnormalities are detected, the checkpoints will sound an alarm among all entities timely. Dynamic traceability solutions thus have high accuracy and good timeliness. As the number of checkpoints influences timeliness, we refine dynamic traceability solutions in the analysis as one-point dynamic solutions, three-point dynamic solutions, and five-point dynamic solutions, indicating one, three, and five checkpoints, respectively, in the supply networks.

As analyzed above, the typical solutions and their technical attributes are summarized in Table 3. Besides, in line with the previous studies (Óskarsdóttir and Oddsson 2019; Gautam et al. 2017), we assume that it requires a very high cost to apply a dynamic solution, a mid-range cost to apply a static solution, and a relatively low cost.

|                         | Traditional | Static | One-point dynamic | Three-point dynamic | Five-point dynamic |
|-------------------------|-------------|--------|-------------------|---------------------|-------------------|
| Accuracy \((A)\)        | Weak        | Medium | Strong            | Strong              | Strong            |
| Timeliness \((T)\)      | Weak        | Weak   | Weak              | Medium              | Strong            |
| Cost \((C)\)            | Low         | Medium | Very high         | Very high           | Very high         |
to implement a traditional solution. The costs of the five traceability solutions are also listed in Table 3.

According to the timeliness and accuracy levels, the scores of traceability solutions on technical attributes are listed in Table 4. The cost levels of different solutions are also given in Table 4.

5.3.2 Disruption mitigation models based on typical traceability solutions

5.3.2.1 Traditional traceability solution Function/internal mechanism: cannot support source identification before the food transformation due to weak accuracy and will not provide warnings of contamination until the contaminated food arrives at the sink node due to weak timeliness.

Input: \( A = 1, T = 1, C = 1, C_B = \text{default}, C_D = \text{default}, SN = \text{default}. \)

Identified contamination source: \( Tn_i \), the transforming node.

Terminal discovery point: \( tp_{12} \), the sink node.

Identified contamination path: \( W_{Tn_i, tp_{12}} \), a segment between \( Tn_i \) and \( tp_{12} \).

Determined IAOC: \( Z^{tradi} \), a region including the contamination path \( W_{Tn_i, tp_{12}} \) and all related transforming \( Tn_i \) and pre-transforming nodes \( Pn_i \).

Output: \( SN' \), a network after removing the IAOC.

An example is shown in Fig. 3.

Thus, the model is:

\[
SN \xrightarrow{tradi} SN',
\]

\( SN = (N, A), (N = \{n_1, n_2, ... n_i\} \land i = 12, A = \{a_1, a_2, ... a_j\}), \)

\( SN' = \{x | x \in SN \land x \notin Z^{tradi}\}, \)

\( Z^{tradi} = \{W_{Tn_i, tp_{12}}, Tn_i, Tn', Pn'\}, \)
Fig. 3 An example of network disruptions under traditional traceability solutions
where $T_{n_i} = W_{1, p_{12}} \cap T_n$, $T_n' = T_n \cap UP_{T_n}$, $P_n' = P_n \cap UP_{T_n}$.

### 5.3.2.2 Static traceability solution

*Function/internal mechanism* support source identification before the food transformation due to medium accuracy and will not provide warnings of contamination until the contaminated food arrives at the sink node due to weak timeliness.

**Input:** $A = 2$, $T = 1$, $C = 3$, $C_B = \text{default}$, $C_D = \text{default}$, $SN = \text{default}$.

**Terminal discovery point:** $tp_{12}$, the sink node.

**Identified contamination source:** $n_1$, the source node.

**Identified contamination path:** $W_{n_1, p_{12}}$, a clear and definite path.

**Determined IAOC:** $Z_{\text{static}}$, limited to the contamination path $W_{n_1, p_{12}}$.

**Output:** $SN'$, a network after removing the IAOC.

An example is shown in Fig. 4.

Thus, the model is:

$$\frac{SN}{\text{static}} \rightarrow SN',$$

$$SN = (N, A), (N = \{n_1, n_2, ... n_i\}, i = 12, A = \{a_1, a_2, ... a_j\}),$$

$$SN' = \{x | x \in SN, x \notin Z_{\text{static}}\},$$

$$Z_{\text{static}} = \{W_{1, p_{12}}\}.$$

### 5.3.2.3 Dynamic traceability solution

*Function/internal mechanism* identify a clear contamination path due to strong accuracy and shorten it between two checkpoints due to the varying timeliness.

**Input:** $A = 3$, $T = 1, 2, 3$, $C = 6, 8, 10$, $C_B = \text{default}$, $C_D = \text{default}$, $SN = \text{default}$.

**Identified contamination source:** $n_i$, the checkpoint upstream from the original contamination point $op_i$.

**Terminal discovery point:** $tp_j$, the checkpoint downstream from the original contamination point $op_i$.

**Identified contamination path:** $W_{n_i, p_j}$, a segment of the path between the two checkpoint.

**Determined IAOC:** $Z_{\text{dyn}}$, limited to the segment of path $W_{n_i, p_j}$.

**Output:** $SN'$, a network after removing the IAOC.

An example is shown in Fig. 5.

Thus, the model is:

$$\frac{SN}{\text{static}} \rightarrow SN',$$

$$Z_{\text{static}} = \{W_{1, p_{12}}\}.$$
Fig. 4. An example of network disruptions under static traceability solutions.
Fig. 5 An example of network disruptions under dynamic traceability solutions.
Food supply network disruption and mitigation: an integrated…

\[ SN^{dyn} \rightarrow SN', \]

Where \( SN = (N, A), (N = \{n_1, n_2, ...n_i\} \quad i = 12, A = \{a_1, a_2, ...a_j\}) \),

\[ SN' = \{x|x \in SN \cap x \notin Z^{dyn}\}, \]

\[ Z^{dyn} = \{W_{n_i, tp_j}\}, \]

\[ n_i = W_{1, tp_j} \cap UP_{op_i} \cap check, \]

\[ tp_j = W_{1, tp_j} \cap DN_{op_i} \cap check. \]

The specific algorithm and code of the above models can be downloaded from the website: https://pan.baidu.com/s/1kn90AAL9qCjf3zBHy1qnTw?pwd=iuti.

6 Fundamental structures of food supply networks

Network structures also relate to the mitigation of network disruptions (Skilton and Robinson 2009).

Scholars have proposed four basic structures in physical supply networks (Rivkin and Siggelkow 2007; Kim et al. 2015): block-diagonal, scale-free, centralized, and diagonal (as shown in Fig. 6). As the diagonal structure typically occurs in military logistics networks rather than food supply networks, this study focuses on the first three network types and their structural attributes.

6.1 Block-diagonal network

A block-diagonal network structure (see Fig. 6a) has a special form of interactions, namely nodes that connect inside clusters and not between clusters (Rivkin and Siggelkow 2007). This feature implies a close relationship between the block-diagonal pattern and the notion of decomposability (Simon 1991). In a supply network context, this may depict emerging agri-food supply networks distinguished by modular supply systems (Sturgeon 2002). For example, “farmer-supermarket docking” is a typical mode that supports modular production and operation in food industries (Mofan and Changta 2017). In this mode, food products under a category are designed as a module. The supermarket acts as the integrator to set food production standards, integrate procurement resources, and sell food products, while selected farmers and professional cooperatives act as module suppliers, each of which is fully in charge of plating, manufacturing, and processing its own module (Mofan and Changta 2017).
Fig. 6 The three basic structures of real food supply networks

- **Block-diagonal structure** $N=12$ $K=1.50$
- **Scale-free structure** $N=12$ $K=2.17$
- **Centralized structure** $N=12$ $K=2.25$
6.2 Scale-free network

A scale-free network (see Fig. 6b) has a power-law node degree distribution, meaning that a few nodes have many more connections than most other nodes (Rivkin and Siggelkow 2007). Thus, this network reflects a “the richer get richer” phenomenon and indicates the presence of large hubs (Rivkin and Siggelkow 2007). In a supply network context, this network pattern describes a situation in which a small number of top-tier suppliers have close relationships and interactions and can also significantly impact supply flows from upstream members (Kim et al. 2015). To the best of our knowledge, this structure emerges in most processed food supply networks (Niknejad and Petrovic 2016). The production and supply of processed foods typically require a focal manufacturer and several core suppliers. These few firms at the heart of the supply network cooperate with each other to jointly control a large number of firms at the periphery of the network (Niknejad and Petrovic 2016).

6.3 Centralized network

A centralized network structure (see Fig. 6c) takes the notion of centralization to the extreme (Rivkin and Siggelkow 2007). In a centralized network, one or very few nodes dominate the entire network through patterned interactions such that a few nodes link to almost all other nodes while the other nodes connect only to the few. In a real food supply network, this structure indicates that a few highly central individuals directly manage and control most other entities (Kim et al. 2015). A real-world example comes from administrative monopoly food industries. In the Chinese pork industry, there is a policy that a government license is required to slaughter and sell pork (Lin et al. 2017). This policy is intended to promote food safety, but in actuality, it promotes the formation of an administrative monopoly (Chen and Yu 2018). The market can only purchase pork from designated firms, and pig farms can only sell pigs to designated buyers. As a result, a small number of entities can manipulate the overall supply network.

The three fundamental networks are adopted to disruption mitigation models. According to the basic assumptions of food supply networks in the models, the number of nodes in the three fundamental networks is set to 12, and the number of source and sink nodes is set to 1. The deviation in the average degree of the three networks is also kept as small as possible so that this analysis can focus on the essential impact of the structures.

6.4 Structural attributes of fundamental supply networks

In the study of Kim et al. (2015), disruptions mitigation has an implied relationship with betweenness centralization ($C_B$) and degree centralization ($C_D$), which are two network metrics. Their definition and formulation are illustrated in the appendix. Here, betweenness centralization and degree centralization are also
seen as structural attributes of food supply networks. The connections pattern in the three networks is adjusted to change their scores on structural attributes (see Table 5).

7 Simulation experiment

7.1 Experimental design

7.1.1 Assumption

In this section, a group of simulation experiments for the disruption mitigation models are conducted. In the experiments, we use a digraph to simulate a food supply network. The occurrence mechanism mentioned above is adopted to simulate the occurrence of disruptions in the food supply network. In each simulation, contamination randomly occurs at any nodes or arcs except the source and sink nodes.

7.1.2 Input variables and parameter values

Input variables are divided into two categories. One is traceability solutions and their technical attributes and cost (the specific parameter values see Table 4). While the other is network structures and their structural attributes (the specific parameter values see Table 5).

7.1.3 Key performance indicator

Besides, mitigation capability is proposed to measure the ability of food supply networks to withstand disruptions. In work by Kim et al. (2015), the “ability of a supply network to withstand disruption” was computed using a simulation model. Building on this method, we calculate mitigation capability by estimating the probability of network disruption non-occurrence when a contamination event occurs randomly on any node or arc of the network. Thus, we use the ratio of the total number of simulations where network disruption does not occur (denoted as $Num^*$) over the total

| Block-diagonal | Scale-free | Centralized |
|---------------|-----------|-------------|
| $C_B = 0.73$  | $C_B = 0.73$ | $C_B = 0.73$ |
| $C_B = 0.82$  | $C_B = 0.82$ | $C_B = 0.82$ |
| $C_B = 0.91$  | $C_B = 0.91$ | $C_B = 0.91$ |
| $C_B = 0.73$  | $C_B = 0.73$ | $C_B = 0.73$ |
| $C_B = 0.73$  | $C_B = 0.73$ | $C_B = 0.73$ |
| $C_B = 0.73$  | $C_B = 0.73$ | $C_B = 0.73$ |
| $C_B = 0.73$  | $C_B = 0.73$ | $C_B = 0.73$ |

$C_B$ refers to betweenness centralization. $C_D$ refers to degree centralization.
number of contamination event simulations (denoted as $Num^T$) in an experiment to represent the mitigation capability (denoted as $MC$). Formally,

$$MC = \frac{Num^*}{Num^T},$$

where, $Num^T$ is set to 20,000 in each experiment.

### 7.1.4 Data collection

Five variables are involved in the data, which are accuracy of traceability solutions ($A$), timeliness of traceability solutions ($T$), cost of traceability solutions ($C$), betweenness centralization of supply networks ($C_B$), and degree centralization of supply networks ($C_D$).

The data of technical variables are collected from the literature review on traceability technology. While the data of structural variables are collected from real food industries. Besides, data biases may come from the simplification on the connections pattern of the real food supply networks.

The original data used in the experiments could be downloaded at the website: https://pan.baidu.com/s/1kn90AAL9qCjf3zBHylqTw?pwd=iuti. What’s more, the limit of the data set is also attached to the original data.

### 7.2 Experimental implementation

The experiments aim to explore the relationship between traceability solutions, network structures, and mitigation capability. The experimental framework is shown in Fig. 7.

---

**Fig. 7** Experimental framework
The experiments start with the adoption of traceability solutions to mitigate disruptions. This part discusses the technical attributes of traceability solutions and the type of traceability solutions. Discussion on the technical attributes makes a specific exposition of the relationship between traceability and mitigation capability, whereas discussion on the type provides an overall understanding of the relationship. Then, network structures are also adjusted to mitigate disruptions in the experiments. Discussion in this part also covers two aspects, one of which is the structural attributes of supply networks and the other is the type of supply networks. A study on the structural attributes also shows a detailed discussion of the relationship between structure and disruptions mitigation, while analysis on the network type takes a comprehensive perspective to illustrate the relationship. At last, we make traceability solutions and network structures work together to withstand disruptions. The joint effects of technical attributes and structural attributes on disruptions mitigation are also discussed in this part. In this way, we can have a better knowledge of the effects of traceability solutions and network structures and their interactions on disruptions mitigation.

8 Discussion and results

8.1 Traceability solutions

As mentioned above, traceability solutions are firstly proposed to mitigate disruptions because they can make up for the shortcomings of traditional methods. Thus, traceability solutions are the first research focus. Table 6 shows the variation of mitigation capability with the change of traceability solutions, which can help us explore the influence of traceability solutions on mitigation capability.

8.1.1 Technical attributes

Initially, we analyze the technical attributes of traceability solutions. In Table 6, accuracy \((A)\) and timeliness \((T)\) both range from 1 to 3. Mitigation capability has shown a rapid increase (from 0.78 to 0.90) when accuracy grows up (from 1 to 3) and timeliness remains unchanged. Then, the increase in mitigation capability slows

|             | Traditional | Static | One-p-dynamic | Three-p-dynamic | Five-p-dynamic |
|-------------|-------------|--------|---------------|-----------------|---------------|
| **A**       | 1           | 2      | 3             | 3               | 3             |
| **T**       | 1           | 1      | 1             | 2               | 3             |
| **C**       | 1           | 3      | 6             | 8               | 10            |
| **MC**      | 0.78        | 0.88   | 0.90          | 0.93            | 0.95          |

One-p-dynamic refers to the one-point dynamic solution; three-p-dynamic refers to the three-point dynamic solution; five-p-dynamic refers to the five-point dynamic solution

\(MC\) refers to mitigation capacity
Food supply network disruption and mitigation: an integrated...

down (from 0.90 to 0.95) when timeliness begins to rise (from 1 to 3) and accuracy keeps constant. The increasing tendency in mitigation capability means that traceability solutions with higher accuracy or timeliness make supply networks more possible to withstand network disruptions. While the increase speed of mitigation capability reflects the different impacts of accuracy and timeliness on mitigation capability. Particularly, the fact that the increasing speed changes from fast to slow indicates accuracy has a more positive effect on mitigation capability than timeliness. The analysis of technical attributes can be summarized as,

Finding 1 (about technical attributes) accuracy and timeliness of traceability solutions both have a positive impact on mitigation capability of food supply networks, although the positive impact of accuracy on mitigation capability is greater than that of timeliness.

Theoretically, finding 1 suggests the positive impact of accuracy and timeliness. This part of the finding is consistent with the recent findings of Chongwatpol and Sharda (2013) as well as MacKenzie and Apte (2017). Finding 1 also reveals the priority of technical attributes of traceability solutions, that is, accuracy is more important than timeliness. While the difference between the impact of accuracy and timeliness on mitigation capability is firstly discovered by this study, which is one of the primary contributions of this paper.

Practically, finding 1 suggests that traceability technology, especially tracing technology, is a powerful and effective tool to mitigate supply network disruptions in the food industry. Recall, there is a corresponding relationship between technical attributes and technical composition. For instance, the accuracy of traceability solutions relies on tracing technology, such as barcode technology or RFID technology. This kind of technology has the ability of automated scanning and batch processing and could recognize the sources of goods accurately. Whereas, the timeliness of traceability solutions is provided by tracking technology, like WSN technology. This technology supports immediate reporting of goods quality information. The advantage of accuracy over timeliness in disruptions mitigation implies that, in practice, food industries should actively deploy RFID technology without abandoning the widely used barcode technology, but carefully employ WSN technology.

8.1.2 Solution type

As for the solution type, a contingent choice method should be applied by food supply networks. Specifically, a traditional traceability solution is the most cost-effective option, because it shows the highest cost-performance ratio ($MC/C=0.78$). Although having bad timeliness, a static solution takes a relatively low cost ($C$ is 3) to generate an acceptable performance ($MC$ is 0.88 shown in Table 6) due to its higher accuracy. Given this fact, a static traceability solution is a balanced option for cost and performance. However, a dynamic solution is an effect-oriented choice considering its highest cost and best performance (such as $C$ is 10 and $MC$ is 0.95). If a supply network attaches the utmost importance to security and stability when facing
network disruptions, dynamic solutions will be its best choice. This section can be concluded as,

Finding 2 (about solution type) a traditional traceability solution is the most cost-effective option, a static solution is a balanced option for cost and performance, while a dynamic solution is an effect-oriented option.

Finding 2 conflicts with researchers who insist that the best technology strategy should be adopted in most cases (Chongwatpol and Sharda 2013; Wattanakul et al. 2018; Wen et al. 2018). The finding could help supply networks to choose prosperous traceability solutions in practice.

8.2 Network structures

Food supply network structures are another important research content because their significant impact on mitigation capability has been confirmed by a lot of research (Kim et al. 2015). Here, we will investigate the impact both from the perspective of structural attribute and network type, which was hardly taken in previous studies. Table 7 illustrates the variation of mitigation capability with the change of network structures.

8.2.1 Structural attributes

We first discuss the structural attributes of supply networks. In Table 7, the situations in different networks are varied, which inspires us to discuss them separately. In block-diagonal networks, mitigation capability is always 1 no matter how structural attributes of supply networks change. For these networks, their structural attributes are of no great significance. While the situation in scale-free networks is changed. Two structural attributes, i.e., betweenness centralization

| Table 7 Network structures and mitigation capability |
|-----------------------------------------------|
| Block-diagonal |  |  |  |  |  |  |
| $C_B$ | $C_D$ | $MC$ | $C_B$ | $C_D$ | $MC$ |
| 0.73 | 0.02 | 1.00 | 0.73 | 0.02 | 1.00 |
| 0.82 | 0.02 | 1.00 | 0.73 | 0.05 | 1.00 |
| 0.91 | 0.02 | 1.00 | 0.73 | 0.09 | 1.00 |
| Scale-free |  |  |  |  |  |  |
| 0.73 | 0.27 | 0.88 | 0.73 | 0.27 | 0.88 |
| 0.82 | 0.27 | 0.94 | 0.73 | 0.31 | 0.87 |
| 0.91 | 0.27 | 1.00 | 0.73 | 0.33 | 0.85 |
| Centralized |  |  |  |  |  |  |
| 0.73 | 0.60 | 0.70 | 0.73 | 0.45 | 0.71 |
| 0.82 | 0.60 | 0.72 | 0.73 | 0.53 | 0.70 |
| 0.91 | 0.60 | 1.00 | 0.73 | 0.60 | 0.70 |
and degree centralization, of scale-free networks both have a significant influence on mitigation capability. For instance, as betweenness centralization gradually increases from 0.73 to 0.82 and 0.91 (degree centralization remains constant), mitigation capability also grows up, which are 0.88, 0.94, and 1.00 respectively. The result indicates that betweenness centralization could positively affect mitigation capability in scale-free networks. By contrast, mitigation capability declines (0.88, 0.87, and 0.85) as degree centralization grows (0.27, 0.31, and 0.33), which indicates that, in scale-free networks, degree centralization harms mitigation capability. However, in centralized networks, the situation changes again. Only one of the structural attributes, i.e., betweenness centralization, could influence mitigation capability and its impact remains positive. The minute change (0.71, 0.70, and 0.70) in mitigation capability caused by degree centralization can be negligible. In all, both two structural attributes could affect mitigation capability in scale-free networks, only one in centralized networks could affect, whereas none in block-diagonal networks could make an influence. The result reflects that the effects of structural attributes exhibit the highest sensitivity in scale-free networks. The discussion on structural attributes is summarized as,

Finding 3 (about structural attributes) betweenness centralization has a positive or no effect on mitigation capability, while degree centralization has a negative or no effect on mitigation capability.

Finding 4 (about structural attributes) the effects of structural attributes show the highest sensitivity in scale-free networks, followed by centralized networks, and least to block-diagonal networks.

Theoretically, finding 3 shows the positive impact of betweenness centralization and the negative impact of degree centralization on disruptions mitigation. While finding 4 demonstrates the high sensitivity of the impacts in scale-free networks. Finding 3 is supported by Skilton and Robinson (2009) and Lu et al. (2019). But the sensitive analysis in finding 4 has not been revealed by previous studies, which contributes to the present literature.

Practically, finding 3 and finding 4 could help supply networks to determine whether their structures should be changed and how to change them when facing network disruptions. As mentioned before, betweenness centralization measures the central tendency of nodes with high betweenness centrality in a network. A node with high betweenness centrality represents a communicator or intermediary firm in a supply network, so a high-level betweenness centralization indicates that communicators in a network connect closely. By contrast, degree centralization estimates the central tendency of nodes with high degree centrality in a network, Because a node with high degree centrality represents a leading firm or focal firm in a network, a high-level degree centralization indicates a centralized distribution of focal firms in a network. Betweenness centralization has a positive effect on mitigation capability because a close relationship between intermediary firms assists in the deep control of information flow and management of network disruptions. Likewise, degree centralization hurts mitigation capability as a close connection between focal firms would greatly increase the network complexity.
As a result, a food supply network in a real world should attach importance to intermediary firms and leading firms. Intermediary firms should work with each other closely to strengthen communication (a higher betweenness centralization) while leading firms should separate from each other to reduce the complexity of entire networks (a lower degree centralization). Thus, a food supply network could keep a high-level mitigation capacity during disruptions. Besides, scale-free networks, where the above impacts shows the highest sensitivity according to finding 4, often emerge in processed food industries, so a processed food industry should pay particular attention to the above practical guidance.

8.2.2 Network type

The comprehensive comparison across three types of networks is different from the comparative study on structural attributes of networks. In Table 7, mitigation capability is highest in block-diagonal networks, all of which is 1.00. Mitigation capability ranges from 0.85 to 1.00 in scale-free networks, which is at the middle level. While almost all values of mitigation capability are below than 0.72 in centralized networks, that is the lowest level. Remarkably, mitigation capability has a huge difference across the three networks. One possible reason is that a block-diagonal network has a simple modular connections pattern, whereas a centralized network refers to highly complex connections. This then affects their mitigation capability. The influence of network type is summarized as,

Finding 5 (about network type) there exists a relatively large difference among the impact of three network types on mitigation capability. Mitigation capability has the highest value in block-diagonal networks, followed by scale-free networks, and lowest in centralized networks.

Finding 5 reports that a block-diagonal network almost has perfect mitigation ability to cope with network disruptions. This depends on the extremely simple and clear network structure as well as the efficient operation regardless of cost. For example, the connections pattern of high-end food supply networks conforms to the definition of block-diagonal structure. These networks adopt the “farmer-supermarket docking” mode to support modular production and peer-to-peer transaction. Simple logistics and business flow make source identification very easy even without the help of accurate tracing technology. Also, almost high-end food industries have deployed mature communication systems and could carry out smooth information exchange even without using real-time tracking technology. Taken together, little structural or technical measures are required to improve the mitigation capacity of block-diagonal networks. Therefore, the following discussion will no longer deal with this network type.
8.3 Joint effects

The joint effects of traceability solutions and networks structures on mitigation capability are the most urgent issues in this study. In this section, we will investigate mitigation capability from both technical and structural perspectives.

Table 8 demonstrates the variation of mitigation capability with the change of accuracy ($A$), timeliness ($T$), betweenness centralization ($C_B$), and degree centralization ($C_D$). For each network type, $A$, $T$, $C_B$, and $C_D$ form into four groups, which are $A$ and $C_B$, $T$ and $C_B$, $A$ and $C_D$, $T$, and $C_D$. The joint effects of the four groups on mitigation capability are discussed separately. The independent effects of $A$, $T$, $C_B$, and $C_D$ are also illustrated in Table 8. For instance, in scale-free networks, mitigation capability with $C_B = 0.73, A = –$ is calculated from the average value of mitigation.
capability with various \( A \) and same \( C_B (C_B = 0.73) \), so that it is only determined by \( C_B \). Besides, the mitigation capability of block-diagonal networks is excluded from the discussion in this section as it is always 1.

The joint effect of \( A \) and \( C_B \) can be investigated through differences in mitigation capability caused by \( A \) and \( C_B \). For example, in scale-free networks, the mitigation capability with \( A = 1 \) and \( C_B = 0.73 \) is 0.84, and the mitigation capability with \( A = 3 \) and \( C_B = 0.91 \) is 1.00. Thus, \( A \) and \( C_B \) jointly increase mitigation capability by 0.16 (0.16 = 1.00–0.84). Moreover, the mitigation capability with \( A = - \) and \( C_B = 0.73 \) is 0.85, and the mitigation capability with \( A = - \) and \( C_B = 0.91 \) is 1.00, which represents \( C_B \) increase mitigation capability by 0.15 (0.15 = 1.00–0.85). Likewise, the mitigation capability with \( A = 1, C_B = - \) is 0.85, and the mitigation capability with \( A = 3 \) and \( C_B = - \) is 0.96. It indicates \( A \) increase mitigation capability by 0.11 (0.11 = 0.96–0.85). In all, the overall difference (0.16) is bigger than the differences caused by the individual factors (0.15 and 0.11) but smaller than their sum (0.26 = 0.15 + 0.11). This result indicates that the joint effect of accuracy and betweenness centralization on mitigation capability is bigger than the independent effects but smaller than their sum. Correspondingly, in centralized networks, we use the same method to calculate the overall difference in mitigation capability caused by \( A \) and \( C_B \). Its result is 0.59 (0.59 = 1.00–0.41), which is also bigger than the differences caused by the individual factors (0.38 and 0.22) and smaller than their sum (0.60 = 0.38 + 0.22). The result of centralized networks reflects the same finding as that of sale-free networks. Thus, the results can be concluded as,

Finding 6 (about the joint effect of \( A \) and \( C_B \)) the joint effect of accuracy and betweenness centralization on mitigation capability is greater than the independent effects but smaller than their sum.

Theoretically, the joint effect of accuracy and betweenness centralization shown in finding 6 implies that the positive effects of timeliness and betweenness centralization on mitigation capacity will decline when they jointly affect disruptions mitigation. The positive effect of betweenness centralization is due to deep connections between intermediary firms (according to finding 3). They work together to administrate information. Whereas, the positive effect of accuracy comes from accurate recognition of goods sources and good arrangement of upstream structure, which is provided by tracing technology (according to finding 1). Tracing technology simplifies network structure but enlarges information amount. Difficulty in information management expands and the positive impact of intermediary firms declines. This is perhaps the reason why the joint effect of accuracy and betweenness centralization is smaller than their sum.

Practically, if a food supply network relies on its intermediary firms to manage information and disruptions, it should apply tracing technology carefully to avoid the conflict between the technology and the intermediary firms.

Next, we choose another two cases to explore the joint effect of \( T \) and \( C_B \). The first one is also in scale-free networks. The overall difference of mitigation capability caused by \( T \) and \( C_B \) is 0.12 (0.12 = 1.00–0.88), the difference caused by the individual factor \( T \) is 0.09 (0.09 = 1.00–0.91), while the difference caused by the
individual factor $C_B$ is $0.02$ ($0.02 = 0.98–0.96$). The overall difference ($0.12$) is bigger than the differences caused by individual factors ($0.09$ and $0.02$) and their sum ($0.11 = 0.09 + 0.02$), which illustrates the joint effect of timeliness and betweenness centralization is greater than the sum of the independent effects. In centralized networks, the second case shows the overall difference of mitigation capability caused by $T$ and $C_B$ is $0.26$ ($0.26 = 1.00–0.74$). The difference caused by $T$ is $0.20$ ($0.20 = 1.00–0.80$), while the difference caused by $C_B$ is $0.07$ ($0.07 = 0.90–0.83$). The overall difference in centralized networks is smaller than the sum of the individual differences. The result in centralized networks shows that the joint effect is smaller than the sum of the independent effects, which is exactly different from that in scale-free networks. In total, the overall difference caused by $T$ and $C_B$ of two cases show different patterns, which represents that,

\textit{Finding 7 (about the joint effect of $T$ and $C_B$)} the joint effect of timeliness and betweenness centralization is changing according to networks types.

In theory, finding 7 summarizes the joint effect of timeliness and betweenness centralization on mitigation capacity.

In scale-free networks, the joint effect is bigger than the sum of the independent effects, which implies the synergistic effect between timeliness and betweenness centralization. The behavior characteristic of intermediary firms in scale-free networks and its reinforcement caused by traceability technology are responsible for the synergistic effect. Intermediary firms are active in a network with high-level betweenness centralization (according to finding 3). Especially when there is a scale-free connection pattern, the firms could almost control information flows across entire of the network to overcome the risk of disruptions (according to finding 4). While a high-level timeliness indicates that the network adopts tracking technology and could support real-time communication (according to finding 1). This undeniably strengthens the intermediary’s control over the network, further improving the mitigation capability of the network, and thus leading to an addictive effect between timeliness and betweenness centralization.

By contrast, in centralized networks, the joint effect is smaller than the sum of independent effects. It reflects the reduction of positive effects of timeliness and betweenness centralization. In other words, the real-time tracking ability of traceability technology and high-level betweenness centralization conflict with each other in centralized networks. The reason for this phenomenon may be the behavior characteristic of intermediary firms in centralized networks. Because of the little number of intermediary firms in centralized networks, high-level timeliness and real-time communication instead increase the activity of non-intermediary firms (such as focal firms or periphery firms). This disrupts the intermediary’s information management and weakens the positive effects of timeliness and betweenness centralization.

In practice, intermediary firms should work together and apply the real-time tracking technology positively in a processed food supply network (usually emerging a scale-free structure); while in an administrative monopoly food supply network (often emerging a centralized connection), real-time tracking technology needs to be used with caution.
Then, it is the turn for the joint effects of $A$ and $C_D$ or $T$ and $C_D$. The two joint effects are distinct from the above joint effects as the impact of $A$ or $T$ on mitigation capability is positive whereas the impact of $C_D$ is mostly negative. Here, we only use the overall difference to analyze how $A$ and $C_D$ or $T$ and $C_D$ influence the mitigation capability together. No matter in scale-free or centralized networks, all of the overall differences of mitigation capability caused by $A$ and $C_D$ or $T$ and $C_D$ are bigger than 0, which demonstrates that the positive effect is greater than the negative effect. Hence, we can get that,

*Finding 8* (the joint effects of $A$ and $C_D$ or $T$ and $C_D$) the positive effect of accuracy or timeliness on mitigation capability is greater than the negative effect of degree centralization, so the joint effects of $A$ and $C_D$ or $T$ and $C_D$ on mitigation capability both are positive.

In theory, finding 8 concludes the joint effect of accuracy and degree centralization or timeliness and degree centralization. A high-level degree centralization negatively affects the mitigation capacity of supply networks because a close relationship and connection between focal firms will sharply increase the network complexity (according to finding 3). Otherwise, a high-level accuracy or timeliness positively affects the mitigation capacity of supply networks as the accurate tracing technology or real-time tracking technology is applied (according to finding 1). The farmer helps to identify goods sources and arrange upstream structures, while the latter assists in information exchange. Both of them can reduce network complexity and counteract the negative effect of degree centralization.

In practice, a food supply network with quite a few focal firms should positively employ traceability technology to withstand network disruptions.

The joint effects revealed in finding 6, finding 7, and finding 8 are the main innovative contributions in this paper because technical attributes of traceability solutions and structural attributes of supply networks were hardly ever considered in a unified framework. Hence, the findings could contribute to theories of disruption management. Besides, in reality, most of the traceability technology is embedded in various networks. The interactions between traceability solutions and network structures could also provide a better knowledge of the adoption of traceability solutions in real supply networks.

9 Conclusions and future works

9.1 Conclusions

Although many scholars have researched supply disruption and traceability, they have largely adopted a purely technical perspective. However, during the epidemic of COVID-19, traceability systems are typically applied in food supply networks or played a role as a network organization. This network attribute of traceability should not be overlooked. Hence, this paper adopted the concept of network disruptions to develop disruption mitigation models in food supply network settings. Traceability
Food supply network disruption and mitigation: an integrated…

The technology and network structure are then unified to mitigate disruptions in a series of simulation experiments.

The findings in this paper show that accuracy makes a more positive effect on the mitigation capability of food supply networks than timeliness due to the different technical compositions behind them; the difference between these effects determines the choice decision of supply networks on traceability solution types. Likewise, betweenness centralization makes a positive effect but degree centralization makes a negative effect on mitigation capability because intermediary firms and focal firms in food supply networks have different behavior characteristics; these effects are both regulated by supply network types and exhibit different sensitivities. As for the joint effect of technical and structural attributes on mitigation capability, the joint effect of accuracy and betweenness centralization is bigger than the independent effects but smaller than their sum; the joint effect of timeliness and betweenness centralization depends on networks type; while the positive effect of accuracy or timeliness on mitigation capability is greater than the negative effect of degree centralization; these joint effects are caused by the complicated interactive effects between technical composition and behaviors of intermediary firms or focal firms.

The main contributions of this study are as follows. First, only robustness and flexibility are seen as disruption management principles in previous literature. While we break through the limitation and regard the accuracy and timeliness as the new principles of disruption management. Second, technical attributes of traceability solutions and structural attributes of supply networks are considered in a unified framework. This study focuses on the joint effects of traceability solutions and network structures, which breaks the trend of only studying traceability from the technical perspective in existing research. Third, we establish the disruption mitigation models on traceability solutions and their technical attributes. The models characterize how typical traceability solutions function during food supply disruptions, which can help us have a more profound understanding of traceability technology. At last, this study formulates the occurrence mechanism and mitigation strategies of network disruption from a practical case, namely the epidemic of COVID-19 in the Xinfadi market. Therefore, the conclusions of this paper are of greater practical significance.

9.2 Limitations and future directions

This study is subject to several limitations and these limitations highlight the need for further research. Firstly, a food supply network is assumed to be fixed once the food supply network is formed. However, dynamic evolution is the normal state of real food supply networks and may affect traceability or network disruptions. A dynamic structure or external environment that is closer to practice should be considered in future research. Secondly, disruption mitigating models of traceability solutions do not fully consider the impact of ordering policy, pricing policy, liability cost, demand uncertainty, etc. Cooperation between suppliers and consumers by controlling the above factors is a common strategy for mitigating supply disruptions. Future research should incorporate the traditional
mitigation strategy along with these influential factors to obtain more interesting findings. More powerful and complex methods should then be applied to develop a more detailed and comprehensive simulation model.

Appendix

The *average degree* is the average number of arcs for all nodes in a network. The metric reflects the complexity of a network as they focus on the number of interactions in the network.

Before giving the notation of *betweenness centralization*, we must introduce node-level betweenness centrality $C_B(n_i)$. This item calculates how often the node $n_i$ lies on the shortest path in a network and is thus defined as:

$$ C_B(n_i) = \frac{g_{k,h}(n_i)}{g_{k,h}}, $$

(1)

where $g_{k,h}(n_i)$ is the number of shortest paths between the source and sink nodes and through the node $n_i$, and $g_{k,h}$ is the total number of shortest paths from the source node to the sink node in a network.

Betweenness centralization represents the betweenness centrality from an entire network perspective. This metric is determined by calculating the average frequency of each node lying on the shortest path in a network:

$$ C_B = \frac{\sum_{i=1}^{n} [C_B(n^*) - C_B(n_i)]}{n - 1}. $$

(2)

Similarly, *degree centralization* is based on node-level degree centrality $C_D(n_i)$.

$$ C_D(n_i) = \frac{d(n_i)}{n - 1}, $$

(3)

where $d(n_i)$ is the number of neighboring nodes of the node $n_i$.

While degree centralization describes the degree centrality of an entire network, which is denoted as:

$$ C_D = \frac{\sum_{i=1}^{n} [C_D(n^*) - C_D(n_i)]}{n - 2}, $$

(4)

where $C_D(n^*)$ is the maximum value of $C_D(n_i)$.

**Acknowledgements** This research is supported by the National Natural Science Foundation of China (71971093, 71810107003, 72132001) and National Social Science Foundation of China(20&ZD126).
References

Anzola D, Barbrook-Johnson P, Cano JI (2017) Self-organization and social science. Comput Math Organ Theory 23(2):221–257

Buchta C, Meyer D, Pfister A, Mild A, Taudes A (2003) Technological efficiency and organizational inertia: a model of the emergence of disruption. Comput Math Organ Theory 9(2):127–146

Bugert N, Lasch R (2018) Effectiveness of responsive pricing in the face of supply chain disruptions. Comput Ind Eng 124:304–315

Chapman P, Christopher M, Jüttner U, Peck H, Wilding R (2002) Identifying and managing supply chain vulnerability. Logist Transp Focus 4(4):59–70

Chebolu-Subramanian V, Gaukler GM (2015) Product contamination in a multi-stage food supply chain. Eur J Oper Res 244(1):164–175

Chen Y, Yu X (2018) Does the centralized slaughtering policy create market power for pork industry in China? China Econ Rev 50:59–71

Chongwatpol J, Sharda R (2013) RFID-enabled track and traceability in job-shop scheduling environment. Eur J Oper Res 227(3):453–463

Cui J (2020) Disinfection and sterilization in Jingshen seafood market. Beijing Youth Daily, p A01

Dandage K, Badia-Melis R, Ruiz-García L (2017) Indian perspective in food traceability: a review. Food Control 71:217–227

Ding L, Yuan H, Hu B (2021) Adopt or not: manufacturers’ RFID decisions for gray marketing in a competitive environment. Comput Ind Eng 151:106957

El Baz J, Ruel S (2020) Can supply chain risk management practices mitigate the disruption impacts on supply chains’ resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. Int J Prod Econ 233:107972

Gautam R, Singh A, Karthik K, Pandey S, Scrimgeour F, Tiwari MK (2017) Traceability using RFID and its formulation for a kiwifruit supply chain. Comput Ind Eng 103:46–58

Han Y, Yang L, Jia K, Li J, Feng S, Chen W et al (2021) Spatial distribution characteristics of the COVID-19 pandemic in Beijing and its relationship with environmental factors. Sci Total Environ 761:144257

Jia X, Sun L (2020) Jingshen seafood wholesale market is no longer open to individual consumers. Beijing Daily, pp A03

Kim Y, Chen YS, Linderman K (2015) Supply network disruption and resilience: a network structural perspective. J Oper Manage 33:43–59

Kumar M, Basu P, Avittathur B (2018) Pricing and sourcing strategies for competing retailers in supply chains under disruption risk. Eur J Oper Res 265(2):533–543

Li M, Shen L, Huang GQ (2019) Blockchain-enabled workflow operating system for logistics resources sharing in E-commerce logistics real estate service. Comput Ind Eng 135:950–969

Lin X, Zhang D, Wang X, Huang Y, Du Z, Zou Y et al (2017) Attitudes of consumers and live-poultry workers to central slaughtering in controlling H7N9: a cross-sectional study. BMC Public Health 17(1):517

Lu X, Horn AL, Su J, Jiang J (2019) A universal measure for network traceability. Omega 87:191–204

MacKenzie CA, Apte A (2017) Modeling disruption in a fresh produce supply chain. Int J Logist Manage 28(2):656–679

Mai N, Bogason SG, Arason S, Árnason SV, Matthiasson TG (2010) Benefits of traceability in fish supply chains—case studies. Br Food J 112:976

Mejjaouli S, Babiceanu RF (2015) RFID-wireless sensor networks integration: decision models and optimization of logistics systems operations. J Manuf Syst 35:234–245

Mofan C, Changta C (2017) Analysis and comparison of operational efficiency of rural E-commerce and farmer-supermarket docking modes. Logist Technol 3:12

Mohammadzadeh N, Zegordi SH (2016) Coordination in a triple sourcing supply chain using a cooperative mechanism under disruption. Comput Ind Eng 101:194–215

Nair A, Vidal JM (2011) Supply network topology and robustness against disruptions—an investigation using multi-agent model. Int J Prod Res 49(5):1391–1404

Niknejad A, Petrovic D (2016) A fuzzy dynamic inoperability input–output model for strategic risk management in global production networks. Int J Prod Econ 179:44–58

Óskarsdóttir K, Oddsson GV (2019) Towards a decision support framework for technologies used in cold supply chain traceability. J Food Eng 240:153–159

Piramuthu S, Farahani P, Grunow M (2013) RFID-generated traceability for contaminated product recall in perishable food supply networks. Eur J Oper Res 225(2):253–262
Rivkin JW, Siggelkow N (2007) Patterned interactions in complex systems: implications for exploration. Manage Sci 53(7):1068–1085
Simon HA (1991) The architecture of complexity. In: Klar GJ (ed) Facets of systems science. Springer, Boston, pp 457–476
Skilton PF, Robinson JL (2009) Traceability and normal accident theory: how does supply network complexity influence the unitary traceability of adverse events? J Supply Chain Manage 45(3):40–53
Storry J, Thakur M, Olsen P (2013) The TraceFood framework—principles and guidelines for implementing traceability in food value chains. J Food Eng 115(1):41–48
Sturgeon TJ (2002) Modular production networks: a new American model of industrial organization. Ind Corp Change 11(3):451–496
Sun Y (2020) Xinfadi market fully recovered. Beijing Daily, pp A09
Wattanakul S, Henry S, Bentaha ML, Reeverarakul N, Ouzrout Y (2018) Improvement of the containerize performance based on the unitary traceability of smart logistics units
Wen Z, Hu S, De Clercq D, Beck MB, Zhang H, Zhang H et al (2018) Design, implementation, and evaluation of an Internet of Things (IoT) network system for restaurant food waste management. Waste Manage 73:26–38
Wu Z, Wang Q, Zhao J, Yang P, McGoogan JM, Feng Z, Huang C (2020) Time course of a second outbreak of COVID-19 in Beijing, China, June–July 2020. JAMA 324(14):1458–1459
Xu S, Zhang X, Feng L, Yang W (2020) Disruption risks in supply chain management: a literature review based on bibliometric analysis. Int J Prod Res 58(11):3508–3526
Zhang J, Liu L, Mu W, Moga LM, Zhang X (2009) Development of temperature-managed traceability system for frozen and chilled food during storage and transportation. J Food Agric Environ 7(3&4):28–31
Zhou P, Shi ZL (2021) SARS-CoV-2 spillover events. Science 371(6525):120–122

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

Lili Wang is a Ph.D. Candidate in the School of Management, Huazhong University of Science & Technology, Wuhan, China. Her research interests include simulation modeling and IoT intelligent traceability system and its application in disruption management.

Bin Hu received the Ph.D. degree in management science and engineering from Huazhong University of Science and Technology, Wuhan, China, in 1999. He is a Professor of Computer Simulation with the School of Management, Huazhong University of Science and Technology, China. His current research interests include Management systems simulation, social computing, and computational organization theory.

Yihang Feng is a Ph.D. Candidate in the School of Management, Huazhong University of Science & Technology, Wuhan, China. Her research interests include NK model, Complex Network and their application in express logistics network.

Yanting Duan is a Ph.D. Candidate in the School of Management, Huazhong University of Science & Technology, Wuhan, China. Her research interests include organizational behavior, simulation modeling and multi-objective optimization and organizational network design, especially in intelligent environments.

Wuyi Zhang received the Ph.D. degree in management science and engineering from Huazhong University of Science and Technology, Wuhan, China, in 2007. He is a Professor at the Faculty of Management and Economics, Kunming University of Science and Technology, China. His research interests include Supply chain management, Knowledge management and Multi-agents modelling and simulation.
Authors and Affiliations

Lili Wang¹ · Bin Hu¹ · Yihang Feng¹ · Yanting Duan¹ · Wuyi Zhang²

Bin Hu
bin_hu@hust.edu.cn
Lili Wang
wll@hust.edu.cn
Yihang Feng
yihang_feng@hust.edu.cn
Yanting Duan
duanyt@hust.edu.cn
Wuyi Zhang
11306002@kust.edu.cn

¹ School of Management, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan 430074, Hubei, China
² Faculty of Management and Economics, Kunming University of Science and Technology, 727 Jingming South Road, Kunming 650031, Yunnan, China