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Adapting supply chain operations in anticipation of and during the COVID-19 pandemic☆

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ABSTRACT

This article investigates the impacts of the COVID-19 pandemic and their proactive mediation by adaptive operational decisions in different network design structures in anticipation of and during the pandemic. In generalized terms, we contribute to the understanding of the effect of preparedness and recovery decisions in a pandemic setting on supply chain operations and performance. In particular, we examine the impact of inventory pre-positioning in anticipation of a pandemic and the adaptation of production-ordering policy during the pandemic. Our model combines three levels, which is not often seen jointly in operations management literature, i.e., pandemic dynamics, supply chain design, and operational production-inventory control policies. The analysis is performed for both two- and three-stage supply chains and different scenarios for pandemic dynamics (i.e., uncontrolled propagation or controlled dispersal with lockdowns). Our findings suggest that two-stage supply chains exhibit a higher vulnerability in disruption cases. However, they are exposed to a lower system inertia and show positive effects at the recovery stage. Supply chain adaptation ahead of a pandemic is more advantageous than during the pandemic when specific operational recovery policies are deployed. We show that it is instructive to avoid simultaneous changes in structural network design and operational policies since that can destabilize the production-inventory system and result in higher product shortages.

1. Introduction

Supply chain (SC) networks can be characterized by an increased complexity and an uncertainty about matching demand with supply during severe disruptions [1–3]. SC resilience is the network's ability to bounce back and recover to reach a desirable state (i.e., a return to the original state, an equivalent state, or a new one) of SC operations and performance [4,5]. SC resilience research has developed a profound body of knowledge to cope with disruptions [6–10].

In the pre-pandemic world, disruptions have usually been studied as events that interrupt material flows in SCs and adversely impact their performance [11,12]. Recent research has offered a variety of useful methods and models to cope with such event-driven disruptions (which we term *instantaneous disruptions,* i.e. single-point-failure disruptive events of instant impact such as fire or tsunami) and to increase SC resilience [4,13–16]. During the COVID-19 pandemic, SC resilience has been stress-tested on a scale unlike any seen before [17–19].

The COVID-19 pandemic has unveiled a new and understudied area of SC resilience, i.e., analysis of SC operations and performance under extremal shocks of exogenous dynamics [1,20–23]. In particular, SC decision-makers were frequently lacking a guidance on how to react to the pandemic. For example, in an interview we conducted with executives from a variety of industries, the Director of Supply Chain Operations at a U.S. based global food manufacturer discussed his company's decision to invest in millions of dollars in inventory in anticipation of the havoc the pandemic was projected to create. Conversely, the Director of Supply Chain Quality at a U.S. based global aerospace and defense company discussed about suppliers being unable to fulfill demand. Orders were cancelled while new suppliers were being vetted as quickly as possible. In other words, firms had a common question to ask: *keep calm or get going*?

Despite the large body of knowledge, there is a gap in our understanding of the exposure of different SC designs and associated adaptation of operational policies in the COVID-19 pandemic setting. Should some inventory be pre-positioned to overcome the

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material shortages during the pandemic? Or would these ad-hoc actions rather lead to some destabilization in the SC and associated bullwhip and ripple effects [24]? Should the SC sourcing and distribution strategies be changed for pandemic times, e.g., should we change from a multi-stage network design to direct deliveries? If yes, when? Motivated by these questions, in this paper we study SC exposure to long-lasting disruptions such as COVID-19 pandemic and the impact of reactive operational strategies on operations dynamics and performance. In particular, by means of this study, we aim to answer the following research questions:

How are different network design structures exposed to the impact of the pandemic and how these impacts can be mediated by adaptive operational reactive decisions in anticipation of and during the pandemic?

We seek to understand how different network design structures are exposed to the impact of the pandemic, and we explore how these impacts can be mediated by decisions aimed at operational preparedness and recovery. This research question is important for multiple reasons. First, our analysis can help managers to understand what should be the lockdown/quarantine policy. Second, we elaborate on the novel research perspective of what ultimately is the value (to business and/or society) of the information on disruption propagation (i.e., the ripple effect) being provided by the propagation of an epidemic/pandemic. We combine in this study the conventional trade-off between *ex ante* inventory investment and *ex post* lost demand by focusing on the value and implications of novel pandemic dynamics as encountered during the COVID-19 times.

We considered three different SC structural designs to increase the validity of the results. The SC designs considered in this study have been frequently used in literature. For example, Tirkolaee et al. [25] studied two-stage distribution network design with perishable products. To extend the existing studies, we then assessed the impact of two operational reactive strategies. First, we analyze "system reset at recovery stage" strategy which is the cancellation of all orders in the planning algorithm during the disruption period in order to avoid backlog accumulation. Many companies ended up facing this strategy as global supply chains shut down. This is certainly not a strategy of choice but during a global pandemic where the world is facing the disruption to the supply chain, this was an action taken by many firms. Second, we examine the impact of building an excess inventory on SC performance in anticipation of a pandemic, and we explore associated inventory dynamics during a pandemic. These decision choices are in line with managers we spoke with about SC decision making in the face of the COVID-19 pandemic in 2021.

The remainder of this study is organized as follows. In Section 2, we describe our problem context and simulation model Section 3. is devoted to experiments and modeling results. In Section 4, we collate major conceptual insights and offer several managerial implications. We conclude the paper in Section 5 by summarizing our major finding and discussing the limitations of our study and the associated future research perspectives.

2. Background and literature review

2.1. Literature related to instantaneous disruptions

Previous research has considered structural designs and process recovery strategies (e.g., prepositioning extra inventory) to be major drivers of SC resilience [13,26–31]. Surveys by Ho et al. (2015), Snyder et al. [32], Hosseini et al. [5], and Aldrighetti et al. [13] provide comprehensive overviews of different SC resilience capabilities and modeling techniques, and show that inventory reservations have been studied as one of the major preparedness measures subject to two-stage and three-stage SC designs.

For a two-echelon SC structure, Khalili et al. [33] studied an integrated production-distribution planning problem with vulnerable paths and nodes. Through a two-stage scenario-based mixed stochastic-possibilistic programming model, the authors investigated the impact of some additional initial production capacity and emergency inventory at the distribution center. Similar problem setting but with three echelons has been studied by Lücker et al. [34]. Considering risk mitigation inventory (RMI) and reserve capacity as preparedness strategies to manage disruption risks, they found out that holding more RMI downstream than upstream can be more reasonable even when the upstream holding costs are lower while it is often optimal to hold more reserve capacity downstream than upstream. Their second interesting finding is that at each echelon RMI and reserve capacity can be considered substitutes while RMI complements reserve capacity at the adjacent downstream stage. Rezapour et al. [35] analyzed the impact of timing of post-warning and pre-disaster stock prepositioning decisions in disasters with an advance warning, such as hurricanes. Their results offer a stochastic optimization-based model for planners to decide on the best trigger time to start the preparedness activities (i.e., prepositioning stocks of emergency goods). Lotfi et al. [36] developed a two-stage robust stochastic multi-objective programming approach to identify risk-aware, resilient and sustainable closed-loop SC network design using Lagrange relaxation.

Simulation has been proven to be a powerful and practice-oriented technique for studying the dynamics of SC under disruptions [8,12,26,37–39]. Analysis of extant literature leads us to the conclusion that structural dynamics and process system dynamics can cause a redundant system inertia that results in disruption overlays (i.e., intersections of operational and disruption risks) and disruption tails [7,40–44]. While the examination of structural design exposure to disruptions is a useful and important analysis for successfully improving network resilience [32,39,45], extant literature points to the importance of process adaptation (e.g., production-ordering policies in the SC).

Process adaptation, while extensively used in practice, has received much less research attention and has been studied using different simulation methodologies [8,24,38,46,47] without an explicit integration of different structural designs. However, the system behavior depends not only on the structural configuration but also on the operational processes (e.g., sourcing, production control, inventory policies; Ivanov et al., 2016; [48–52]). Product specifics are also important to consider — for example, product perishability in the case of food or healthcare SCs [53,43].

2.2. Literature related to pandemic disruptions

Triggered by the COVID-19 pandemic, SCs experienced a series of shocks and collapses on a scale unlike any seen before [54,55]. The research community has addressed this novel setting by attempting to understand the antecedents and specifics of these new large-scale disruptions with complex dynamics (which we term *super disruptions*) and how they affect SCs [21,45,56–59]. Queiroz et al. [60] point to preparedness with a focus on pre-allocation of some resources and structural re-allocations of supply and demand as two major strategies to cope with an upcoming pandemic. Ivanov and Dolgui [57] showed that adaptation of networks structures and associated production-inventory control policies at individual firms are important determinants of supply chain resilience under pandemic conditions. Hosseini and Ivanov [61] used Bayesian networks to develop an approach for assessment of the pandemic impacts on SC performance.

We further deduce some key characteristics of a pandemic as a super disruption from our literature analysis following structures proposed in various studies (e.g., Craighead et al. 2020, [21,62,63]). Unlike the instantaneous disruption, a pandemic is not an event that strikes and disappears; the pandemic is a super disruption with unknown timing and up/down scaling that is considered exogenous to the SC network [64,65]. This uncertainty results in a unique setting where recovery happens in the presence of the exogenous dynamic of a disruption. As such, the pandemic dynamics can be considered as a separate system that interacts with the SC system and simultaneously influences its network design structures, capacities, supply, and demand [66,60,67].

Ivanov [21] simulated a four-stage global SC measuring the service level, lead time, and fulfilment rate as indicators to understand the impacts of the COVID-19 pandemic on SC performance. Building upon three scenarios of the ripple effect (i.e., disruption propagations) and assuming some variation in intensities of pandemic control measures and pandemic dispersal across the continents, Ivanov [21] observed that the timing of the closing and opening of facilities at different echelons with some overlapping time windows is one of the key factors influencing SC operations and performance under pandemic conditions. Singh et al. [68] simulated a food SC resilience in the COVID-19 pandemic context. The authors observed that SC service level can be improved by centralization of sourcing under pandemic disruptions. A common outcome of studies by Ivanov [21], Ivanov and Das [69], and Singh et al. [68] was the observation that SC operations and performance undergo drastic degradation under the pandemic conditions, thus positing the need for operational policy adaptations in production-inventory control.

Along with simulation, optimization approaches have been frequently used. For example, Tirkolaee et al. [70] developed a mathematical model to design a sustainable mask Closed-Loop Supply Chain Network (CLSCN) during the COVID-19 outbreak. Their multi-objective mixed-integer linear programming (MILP) model addresses the locational, supply, production, distribution, collection, quarantine, recycling, reuse, and disposal decisions within a multi-period multi-echelon multi-product supply chain. A genetic algorithm was used to solve the proposed model and to find Pareto optimal solutions. Paul et al. [71] used optimization for analysis of recovery policies under COVID-19 pandemic disruptions.

Another important research stream has been focused on developing methods for forecasting the pandemic dynamics with consideration of control measures (see e.g., [72–76]). Robust optimization methods have been frequently used in combination with methods based on regression analysis, e.g., using non-parametric regression models like variations of MARS (multivariate adaptive regression splines) [77] for assessing the process dynamics and forecasting. The polynomial structure of MARS regression models helps to predict non-linear dynamics in a more precise way. There are a few research articles devoted to the application of these predictive models for COVID-19 propagation. Lotfi et al. [78] proposed a robust polynomial regression model for estimation of new COVID-19 cases dynamics on a country level. The model is tested on statistics from Spring 2020 (at the early stage of the COVID-19 pandemic). The authors state that the model can be applied to relatively small datasets because the model requires intensive calculations to achieve higher accuracy. Khalilpourazari and Hashemi Doulabi [73] applied a robust modeling approach based on a stochastic fractal search algorithm. Similar to the basic epidemic propagation models, they use contact rate as the main parameter affecting propagation. Kapoor et al. [79] provide a systematic review of COVID-19 influence on manufacturing. They emphasize the importance of correct policies and operational strategies for SCs to withstand the pandemic impact. The general conclusion is that current manufacturing systems are rather fragile to the pandemic disruption. The authors stress the importance of coordinated actions and information exchange among stakeholders.

The findings from the analytical and simulation studies are echoed and extended in extant empirical literature that explores antecedents and consequences of the pandemic-induced SC disruptions and suggest strategies to improve. Elbaz and Ruel [55] utilised a resource-based view and organisational information processing theory to examine the mitigating role of SC risk management practices during the COVID-19 pandemic. They conclude that recovery strategies are critical to ensure SC resilience at the pandemic times. Wieland [63] proposed a panarchy framework that is organized around adaptive cycles linked on scales of time, space, and meaning. Wieland points to the central role of SC structure and process reconfigurability to survive at pandemic times which is in line with the reconfigurable SC framework by Dolgui et al. [40] and viable SC framework by Ivanov [45].

One of the challenges for SC management at pandemic times is simultaneous consideration of disruption dynamics, operational policies, and recovery planning. Nagurney [80] shows that pandemic dynamics can induce labor constraints leading to reductions in SC productivity and capacity. Besides, consideration of some product specifics such as perishability can add additional complexity to the decisions on inventory pre-positioning in anticipation of a long-term crises [81,68]. However, reactive decision-making on SC preparedness to an upcoming pandemic and guiding the SC through the pandemic by proactive adaptation of its network structures and operational production-inventory control policies has not been studied so far with consideration of perishable products, and none of the existing studies examined how different network design structures are exposed to the impact of the pandemic, and how these impacts can be mediated by operational preparedness and recovery decision-making – a distinct and substantial contribution made by our study.

Our analysis shows that current literature lacks an understanding of SC dynamics and recovery behaviors as a reaction to the dynamics of an external system (i.e., a pandemic super disruption). Our study makes several important and distinctive contributions to understanding SC resilience to super-disruptions such as a COVID-19 pandemic. First, we consider the pandemic dynamics as a separate system (and not as a singular disruptive event) that interacts with the SC system and influences its capacities, supply, and demand. In doing so, we explore, SC dynamics and behavior as a reaction to disruptions caused by an epidemic outbreak. Second, we investigate SC reactions to the pandemic as subject to three dimensionalities: network design, process control policies, and the different scenarios of a pandemic. Thus, we triangulate the adaptation analysis by integrating structure-process dynamics with exogenous environmental dynamics. Third, we assess the impact of two recovery strategies with regard to the disruption impact on inventory dynamics in the SC during the disruption and the recovery.

3. Problem context and simulation model

In this section, we describe the problem context and simulation model.

3.1. Problem context

In our problem, a retailer needs to source various products from the suppliers using three possible sourcing systems, i.e., either directly, through an intermediate warehouse, or through a cross-docking system with consideration of the efficiency and service level targets. The available capacities at different SC echelons depend on the number of workers, which may vary due to the pandemic dynamics - decreasing in the case of rising infections and increasing during recovery. The production and inventory are controlled dynamically based on demand and available capacity.

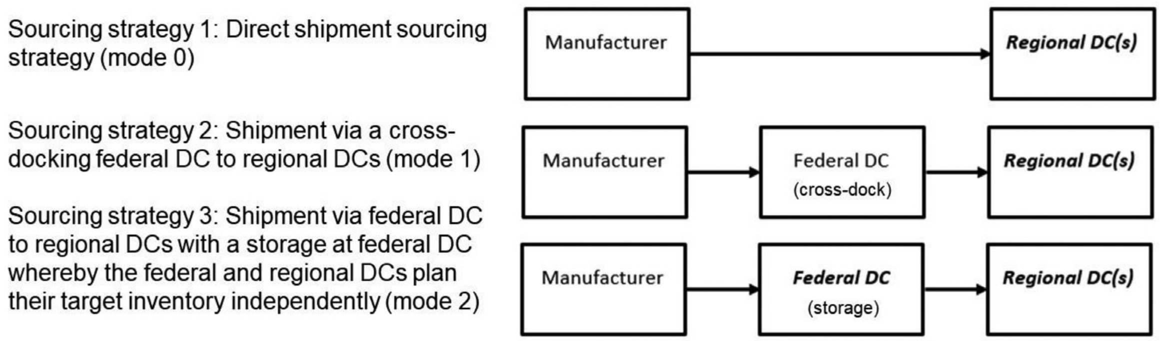

Fig. 1. Supply chain structures and sourcing strategies for analysis.

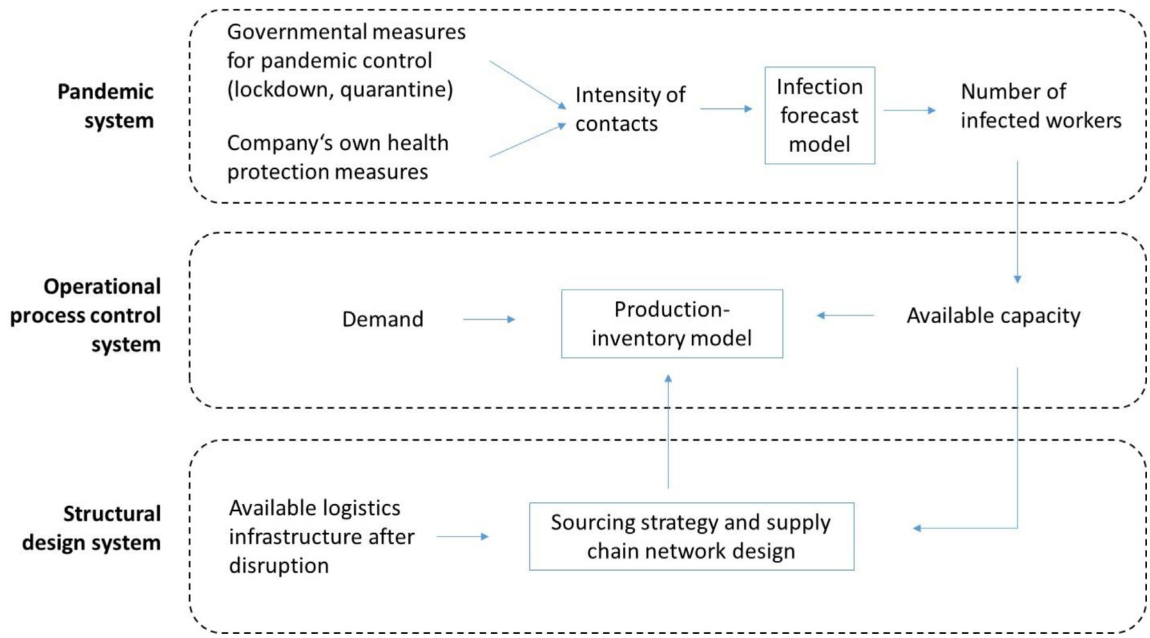

Fig. 2. Problem setting.

From the standpoint of the SC managers, the problem considers how three different SC network designs are exposed to the COVID-19 epidemic outbreak in light of pandemic control actions and a firm's reactive strategies. Our problem and the SC network are based on the real-life context and data of a food retail network operating about 8000 stores spanning five different time zones. The network is managed using numerous distribution centers (DC). During the outbreak of the COVID-19 virus and the associated pandemic, the firm analyzed the exposure of their three major sourcing strategies to the pandemic (Fig. 1).

We consider two scenarios of governmental and company pandemic control: (a) no action to control the epidemic propagation and (b) monitoring the contacts of infected persons, lockdowns, and quarantine measures. Such settings increase the complexity of SC processes due to the uncertainty and dynamics of an exogenous system, that is, the pandemic control. As for SC reactive strategies, the following options have been considered: (a) a "system reset" (e.g., cancellation of all orders in the planning algorithm at the end of disruption) and (b) building excess inventory in anticipation of a pandemic. In Fig. 2, we summarize our problem setting.

Our study focuses on three aspects: (1) analyzing the exposure of three major structural SC designs to pandemic dynamics and its control, (2) understanding how different network designs could be impacted by pandemic disruption with and without deployment of some reactive strategies, and (3) providing recommendations for associated structural changes and process recovery strategies in anticipation of an impending pandemic. In the pandemic dynamics system, governmental and firm's control measures determine the intensity of contacts which is used in an agent-based infection forecast model to predict number of available workers and the resulting available capacity for the operational process dynamics model and sourcing strategies considered (see Figs 1 and 3). The primary problem consists of revealing the operational and performance dynamics of different SC designs under COVID-19 pandemic dynamics and different operational recovery policies in order to decide (i) if a SC design structure and associated sourcing strategy should be changed or not in the wake of a pandemic and (ii) which operational recovery policies should be used based on its performance impact measured by financial (e.g., costs), customer (e.g., service level), and operational (e.g., inventory backlog) indicators.

The following assumptions are considered:

- SC design structure does not change during the modelling time horizon;
- products have some expiration date and cannot be sold thereafter
- instantaneous disruptions are modelled as an immediate event that decreases system output by a given fraction
- epidemic dynamics and forecast depend on the pandemic control measures, i.e., stricter control measures result in lower con-

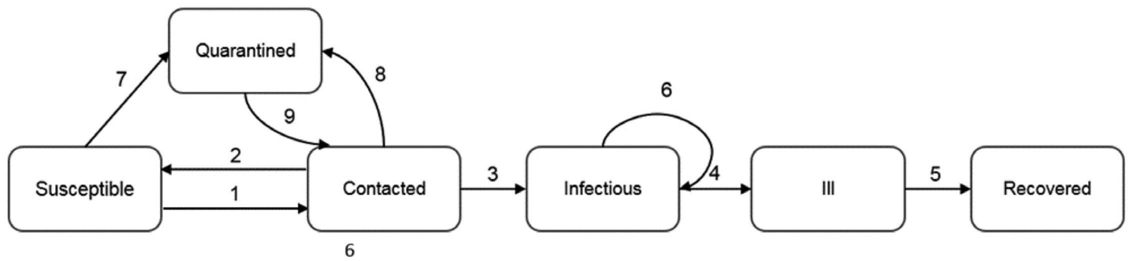

Fig. 3. Agent statechart.

tact intensity, which in turn influences the number of infected workers and the capacities
- experiments are based on a synchronized profile of the infections and productivity, i.e., the output rate is proportional to the number of workers.

3.2. Simulation model

We designed a simulation model based on analytical models of perishable inventory control and using real company algorithms for inventory-production control. In this section, we operationalize the operational SC model and pandemic model, show their interactions, and specifics for different structural network designs.

To undertake the investigation, we view a SC network as a multilayer system composed of structural designs and processes that are interacting with an exogenous, long-lasting super disruption (see Fig. 2). Our model considers two interacting systems and their dynamics, i.e., SC operational processes and the pandemic dispersal for three SC structures and associated sourcing strategies. Disruption propagation and the recovery are modeled under conditions of the operating operational system (i.e., SC network) and following the forecasts of epidemic dynamics in terms of the expected number of infected people using an infection forecast model. This allows for observing inventory dynamics in the SC.

The epidemic dynamics are modeled as a separate, parallel control loop. This property makes it possible to model different situations of an epidemic: when the outbreak happens simultaneously at all SC echelons, or when the outbreak happens sequentially with different timing. This is an important modeling feature because recent studies recognized that the SC performance reaction to pandemic disruptions depends on the timing and scale of disruption propagation (i.e., the ripple effect) as well as the sequence of facility closings and openings at different SC echelons [21]. Thus far, the combination of the velocity of pandemic propagation, the duration of quarantines and lock-downs of production, distribution, and markets, and the degree of demand decline are important determinants when modeling SC networks under pandemic [69]. The pandemic modeling results are fed into the SC model control loop determining dynamic changes of the available capacity and inventory.

3.2.1. Operational SC dynamics model

In this section, we describe analytical model which is used for simulations of SC dynamics. When modeling operational SC dynamics, we build on and extend the simulation model offered by Ivanov and Rozhkov [43] and utilized by Ivanov [45] and Dolgui, Ivanov, and Rozhkov [24]. In particular, we extended the model from a two-echelon setting to a three-echelon setting; next, we added the external control loop, that is, the pandemic dynamics modeling; finally, we included the agent-based modeling of epidemic dispersal.

We utilize a specific production-inventory control policy with consideration of perishability of products close to the generic model for periodic-review perishable inventory control from Nahmias [[82], chapter 2]. To mimic this control policy, we developed a production-inventory control algorithm for simulations which is composed of two parts, i.e., processing of actual customer orders and planning future deliveries. Depending on the sourcing strategy, RDCs are supplied either from the inventory batch i at the federal DC (FDC) (modes 1 and 2 in Fig. 1) or by direct shipments from manufacturer (mode 0). Demand d_t may vary across t-periods with some standard deviation δ_t^{ST} subject to uniform distribution which has been identified through the use of a descriptive analytics algorithm for time-series analysis using past sales data. Lead time L is fixed. $L = L_{RDC} + L_{FDC}$ for the three-echelon SC, and $L = L_{RDC}$ for the two-stage SC (Eq. (1)).

$$L_{three\ stage} = L_{RDC} + L_{FDC};\ L_{two\ stage} = L_{RDC} \tag{1}$$

Product shelf life is defined as η, and inventory freshness level (in days) at supply chain echelon facing customer demand is λ. The λ^{max} is calculated as shown in Eq. (2):

$$\lambda^{max} = \ \eta - L. \tag{2}$$

Each SC echelon has a restriction on the minimum remaining freshness level ρ (i.e., shelf life threshold) that defines a minimum acceptable fractions of the remaining shelf life of a product. For example, $\rho = 0.4$ means that the remaining shelf life threshold is 40% as compared to η. If inventory batch freshness level λ does not meet constraint (3), it will not be shipped downstream the SC. For three-echelon setup (mode 2):

$$\lambda > \rho_{RDC} \times \eta - \ \rho_{FDC} \times \eta + L \tag{3}$$

On-hand inventory batches i are sorted in the simulation model following FEFO (First Expired – First Out) policy and so forming a set $I = \{i_1, i_2, \ldots,\ i_\lambda\}$. Each inventory batch is characterized by two dimensions, i.e., quantity i and freshness level λ [83].

When deciding on the order quantity planning, the model exhibits the well-celebrated order-up-to-level inventory control policy [84,85] which is extended by constraints on the shelf life (1) and (2) following the Nahmias's [82,86] approach. Order quantity planning procedure is based on future shipments and inventory dynamics. Future shipments set $J = \{y_t,\ y_{t+1},\ \ldots,\ y_{t+\beta}\}$ consists of orders y_t previously placed during order fulfilment cycle β. Note that $\beta = L$ for three-echelon SC and $\beta = L + \ \varepsilon$ for shipments from manufacturer without inventory holding at FDC, where ε is production freeze time. In basic configuration orders can be placed every simulation period.

Expected inventory future state set I^p for each planning period $b,\ b \in (t,\ t+\beta)$ is defined by iterative merging of sets I and J according to the rule that each future shipment y from the set $\boldsymbol{J}$ satisfies the constraints (1) and (2). Parameters S_{RDC} and S_{FDC} define target inventory level (i.e., order-up-to levels) for RDC and FDC, respectively. Order $y_{t+\beta}$ is placed if forecasted inventory on hand at period $t+\beta$ meeting constraint (2) is below the target inventory level [87]. Order size is a multiple of the minimum order size ϖ

as shown in Eq. (4).

$$y_\beta = \varpi \times ceil\left(\frac{S - I^p_{t+\beta}}{\varpi}\right) \tag{4}$$

Perishability is taken into account at manufacturer echelon, too. The allocated order $y_{t+\beta}$ placed by the FDC or the RDC (depending on the sourcing strategy) is forwarded into a manufacturing queue at the manufacture. At each period t, z-production batches ($z \in Z$), based on $y_{t+\beta}$ order size are sorted upwards according to production dates F_z. For stabilization, the order is removed from shipments or the manufacturing queue if it cannot be processed at the period of planned order receipt/production subject to limited transportation and production capacities and associated constraints on the queue lengths. Orders from the regional DCs to federal DCs are cancelled if the expected delay in their fulfillment exceeds the order fulfillment cycle time β to avoid the order backlog between SC echelons. If the computed production period of a batch is reached, the orders enter the manufacturing system. Processing start times are based upon the scheduled production period. Early production, i.e. schedule smoothing, is not allowed.

For performance analysis, we consider two indicators, i.e. costs and service level. Total costs are comprised of usual inventory holding costs, transportation costs, write-off costs, penalty (backlog) costs, and manufacturing costs. Inventory with expired dates induces write-off costs which increase proportionally to the purchasing prices p. If the customer order size exceeds the inventory at DC, a penalty u is applied. Manufacturing costs include both variable and fixed setup costs. Overtime capacity is not considered. Service level is measured as a ratio of the on-time delivered orders to the total orders placed.

Disruptions in the model affect manufacturer capacity. Denote the installed capacity at a manufacturer and its disruption coefficient during the pandemic by K and ξ, respectively. As such, the maximum capacity during the pandemic K_{pan} is constrained as

$$K_{pan} = K \times \xi, \tag{5}$$

where ξ is dynamic. It results from the pandemic simulation model and depends on the available workforce and severity of the pandemic control measures imposed by governments and the company itself. In this way, we couple the pandemic and SC dynamics.

In summary, the SC as considered for modeling is quite efficient in terms of inventory dynamics and order quantity planning. This is also in line with extensive literature results on the order-up-to level policies and perishable inventory control in two- and three-stage SCs [85,88–91]. The planning algorithm considers product expiration dates when deciding on ordering and recovery strategy adaptations. The constraints on perishability directly influence the inventory planning decisions, the selection of recovery strategies, and the timing of recovery strategy deployment because building an inventory in anticipation of an epidemic dispersal might be complicated by product expiration dates.

3.2.2. Pandemic dynamics model

We model pandemic dynamics as a multi-agent system. An agent population is assigned to each object in the SC, which forms the epidemic dispersal process. Another key component of our model is that depending on the agent population states (e.g., infected/quarantined), the process control logic of the SC object (e.g., a DC) and its structural interactions with other agents are adapted (if needed). The pandemic is modeled in two modes: with and without epidemic control measures. Each SC node (e.g., DC) is associated with a population of agents that are getting infected depending on the intensity of their contacts, which is determined by the epidemic control measures imposed by the governments (e.g., quarantines and lockdowns) and the company's own protection measures (e.g., tracking the contacts of infected employees). The lower the contact intensity, the lower the number of infected workers, and the higher the available capacity. Using this logic, the number of infected people is forecasted using an embedded infection forecast model, so the varying capacity is included in the process adaptation through production-inventory control algorithms (see further in the paper). We employed agent-based method to implement infection forecast model control loop in order to capture epidemic propagation in a more precise way. To aid in clear result interpretation without losing the reality of the context, we do not include varying intensities of lockdowns (e.g., a full lockdown or a partial lockdown) or the duration of lockdown periods (i.e., we model only a single lockdown period with epidemic control measures of a steady intensity).

Agent statechart allowed to trace contacts of infected agents in a model and implement quarantine measures modeling. The agent statechart is presented in Fig. 3.

The initial infection source is external to a system. Then infectious agents contact susceptible agents with a predefined contact rate. These contacts are modeled as sending of messages by transition 6. After receipt of a message (transition 1), an agent can get the infection and follow transition 3 or stay in a normal state with transition 2. The result is defined by the infection probability parameter. Transitions 4 and 5 are defined by no symptoms period duration and expected illness duration, respectively. Quarantine (transitions 7 and 8) is imposed on all traced agents which were contacted by infectious agents. The quarantine list is updated every period. Transition 9 is defined by quarantine length. The quarantine loop is activated only in case of application of external epidemic control measures.

4. Experiments and results

In our empiricaly grounded problem setting, the company is interested in predicting how three different SC structural designs (i.e., three different sourcing strategies) will react to a pandemic in order to discern if and when structural changes might be needed. To this end, we individually model SC inventory dynamics and performance impacts in each of these three sourcing network designs. Based on this analysis, we then build an overarching perspective that derives managerial implications about the positive and negative effects of transitions between structural states.

Our model was implemented in AnyLogic that conveniently combines agent-based modeling for pandemic dynamics and discrete-event modeling for SC dynamics. For experiments, we divided the disruption modeling into two categories: impact and recovery for (a) a conventional setting (instantaneous disruptions: Profile I) and (b) the COVID-19 setting (super disruptions: Profile II). In Profile I, SC operations during the disruption period and the recovery are not influenced by any exogenous systems and are guided by a given and static level of capacity degradation and restoration. In Profile II, SC operations during the disruption period and the recovery are influenced by an exogenous system (i.e., the pandemic super disruptions) and are guided by forecasting the capacity degradation and restoration according to the dynamically changing epidemic states at SC echelons (e.g., quarantine measures and lockdowns). With the differentiation of these two disruption profiles, we sought to explore the specifics of the pandemic-like disruption profile, and if the results would be different or similar as compared to a single-event instantaneous disruption [24,42]. For both disruption profiles, we intended to observe SC reactions and examine their differences and commonalities. Another rationale for simulating with two different disruption profiles is the possibility that the gradual growth of the disruption scale in a pandemic super-disruption may allow for time to adapt both SC structures and process planning policies.

Table 1
Modeling parameters.

Parameters	Value
Production order size and RDC order size, units	1000
FDC order size, units	5,000
Production capacity, units	30,000
Production cost per unit	0.5
Production interval, periods	1
Production freeze time, periods	2
Base demand at RDC	2,000
Demand variation per period	0.5
Inventory holding costs at RDC	0.02
Inventory holding costs at FDC	0.005
Transportation costs at RDC	0.5
Transportation costs at FDC	0.1
Wastage cost per unit	1.5
Target stock RDC and FDC, respectively, in periods	3
Shelf life, periods	30
Shelf life threshold RDC	0.4
Shelf life threshold FDC	0.6

Table 2
Pandemic Modeling.

Parameters	Value
Total agent population	1000
Contact rate, per period	1
Contact tracing accuracy	1
Infection detection delay, periods	1
Infection probability in case of a contact with infected agent	0.5
No symptoms duration, periods	5
Illness duration, periods	21
Quarantine duration	14
External infection rate	0.005

The disruptions were modeled twofold. First, we ran simulations for instantaneous disruptions. Second, we ran simulations for a pandemic disruption and considered two scenarios of the government's and the firm's policy to control the epidemic, which were (a) no action to control the epidemic propagation and (b) monitoring infected persons' contacts and quarantine measures/lockdowns. The following parameters have been used: 200 periods for the inter-disruption interval and 60 periods for the duration of disruption. The capacity K is recovery to normal at the end of the disruption period. Fixed disruption time was used for the comparison of different policies' resilience capabilities shown in Table 1. The particular set of parameters for simulations has been obtained for a specific product. The data for analysis was approximated from real company data and sensitivity tests have been run to confirm the validity of the proposed model (see Section 4.4).

We used an agent-based implementation of the generic infection forecast model for analyzing epidemic propagation and its influence on system resilience. The infection forecast model is linked to quarantine measures, i.e., quarantine duration is essential for the intensity of contacts and the resulting number of infected agents. The epidemic starts at period 100. We limited epidemic propagation to the manufacturer's site (Table 2).

4.1. Instantaneous disruptions (Profile I)

This set of experiments compared the impact of instant disruptions (Profile I) on SC operations and performances for different structural network designs. We considered a disruption of 50% of factory (i.e., supplier) capacity. The conditional expectation of demand for one period at the RDC was 20,000 product units, and we considered 5 customers for each RDC with a demand expectation of 2,000 units of two different products for each customer. Therefore, under normal conditions the factory has a 50% capacity reservation to compensate for daily demand deviations. Under a disruption of 50% of capacity, we have a deficit of 25%, which leads to the situation in which the orders are fulfilled but the inventory is decreasing quickly. In this setting, we were able to observe the initial system reaction to the disruption and the system stabilization during the recovery after capacity restoration.

In the case of a two-stage SC and direct shipments from factory to RDCs, we observed inventory piling (i.e., the disruption tail or postponed redundancy; [42,43]) during the recovery period (reaching its peak in the period 279). The system reset can compensate for this disruption tail and localize disruption propagation. In the case of a three-stage SC and cross-docking shipments via a FDC, we observed a similar behavior (see Fig. 4).

The differences between the two-stage system and the three-stage system can be explained by different total cycle times from order placement to delivery. The SC network with three stages and holding inventory in both FDC and RDC performed differently and was exposed to the ripple effect (Ivanov, Sokolov, & Pavlov, 2014; Dolgui et al., 2018; [49,92]). The process adaptation to a product deficit caused by production capacity disruption is therefore dependent on the structural network design. This result can be explained by a combined push-pull ordering system in the network design with inventories at both the FDC and RDCs (see Fig. 5).

The FDC adapts to a cross-docking mode during the disruption (periods 226–276). Inventory holding at both FDC and RDCs stimulates the instability of inventory dynamics during the recovery. For example, in the case of a product shortage of 30,000 units, FDC and RDCs can independently place two orders of 30,000 units each, leading to disproportional production planning at the factory, which would plan to double the production quantity. This finding confirms the results demonstrated on the intersection of the structural and operational disruptions [24,46], and emphasizes the importance of differentiated consideration of forward and backward ripple effects [50].

4.2. COVID-19 pandemic super disruption (Profile II)

A pandemic outbreak begins gradually and locally, and its dynamics can be forecasted, for example, by using infection forecast models. The recovery is also gradual. We were interested in examining how this specific disruption profile would influence the insights obtained in Section 3.1. The experimental set in this section followed a synchronized profile of the infections and productivity. In the model, an agent population was allocated to the SC objects (i.e., DCs and the factory) that has been exposed to the pandemic super disruption. The operational policies at SC objects were interlinked with the infection model. Two major configurations of our model were analyzed: with and without governmental quarantine mandates (Fig. 6).

In Fig. 6, we visualize the inventory dynamics for structural designs of Modes 0 and 1. We observed a similar behavior in Modes 0 and 1, namely that the inventory increased after the capacity recovery. Notably, the quarantine / contact tracing measures had a positive effect because a capacity disruption was not observed. We were aware of some simplification of reality in this assumption. Indeed, in real life, in some cases 10% of the missing (infected) workforce can result in a 10% decrease in productivity; in other cases, a 20% workforce reduction can lead to a full shutdown or the closure of an SC object. However, this nonlinear relationship has never been reported in literature, and we did not find any empirical evidence describing this relationship. The agent-based modeling paradigm allowed for a convenient embedding of the pandemic dynamics model into the SC operational model. We observed similar effects in Mode 2 (shown in Fig. 7).

Finally, we performed a set of experiments that considered a recovery strategy of building an excess inventory at the beginning of an epidemic outbreak to avoid the disruption impact on the SC.

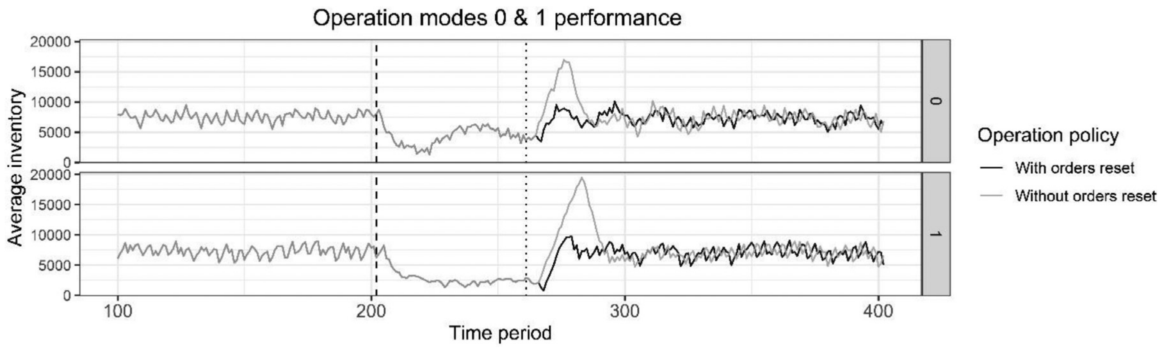

Fig. 4. Supply Chain Reaction to Instantaneous Disruption in the Modes 0 and 1.

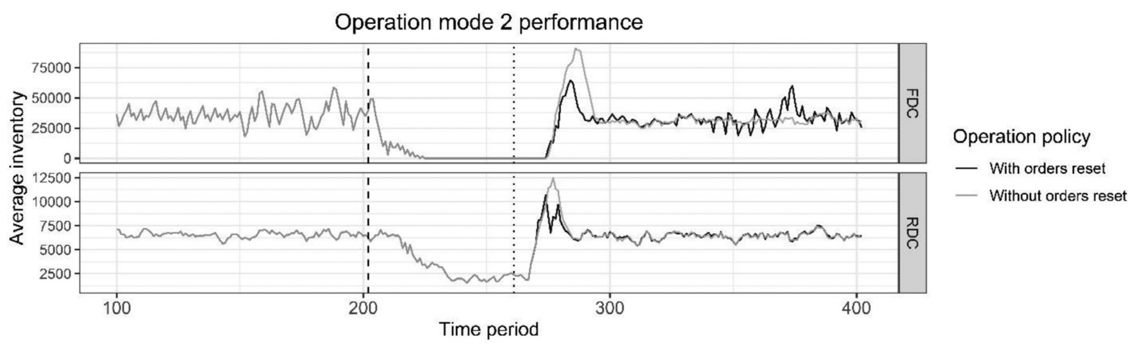

Fig. 5. Supply Chain Reaction to Instantaneous Disruption in the Mode 2.

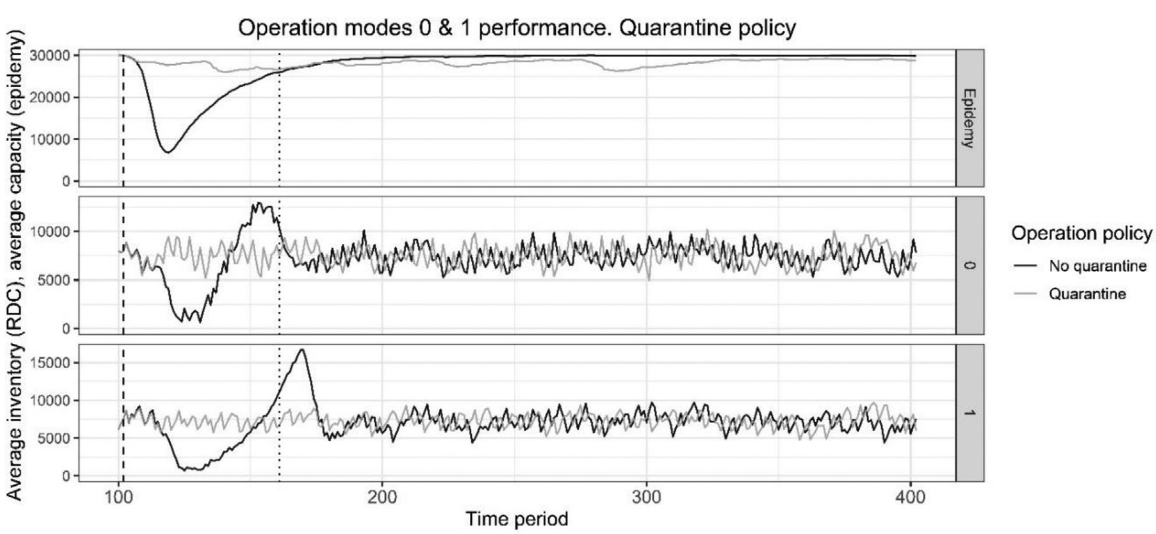

Fig. 6. Capacity Disruption due to Pandemic Dynamics.

The inventory quantity was constrained by the target level of our inventory control policy and the perishability factor. The start of a pandemic super disruption was judged based on the rule that 1% of the agent population had become infected; the end is based on the rule that 50% of the agents have recovered. We illustrate the results of Mode 2 in Fig. 8.

First, we studied the situation in which inventory increased at only one echelon (i.e., either at the RDC or at the FDC). Period 103 and 134 correspond to the beginning and ending of the first pandemic super-disruption wave. Building an excess stock at the beginning of the epidemic contributed to system stabilization. There was an inventory increase at RDC during the recovery that was followed by a higher inventory increase at the FDC. Moreover, we saw similarities in inventory profiles at RDCs and FDC when compared to the disruption Profile I (see Section 3.1 and Fig. 4). As such, we concluded that the inventory increase at the beginning of the pandemic did not bring any additional destabilization in the SC recovery. When we simultaneously increased inventory at both the RDC and the FDC, the system built a buffer inventory downstream the SC. Additional inventory at the FDC was not created, as shown in Fig. 9.

In summary, Figs. 7–9 demonstrate that in the case of inventory shortage, a three-stage SC with two planning echelons transforms to a “virtual” cross-docking operational logic with no stock at the intermediate stage. This can be treated as a type of adaptation, but in reality a sourcing policy switch would lead to lost orders because of manufacturing “freeze time” and would entail higher SC lead times because of new cross-dock planning.

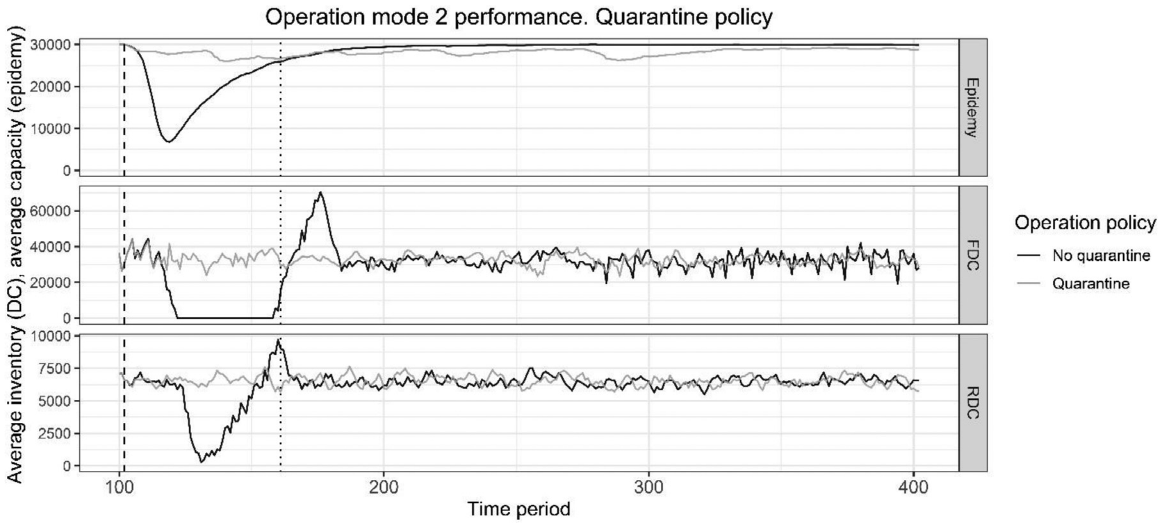

Fig. 7. Inventory Dynamics for Structural Design Mode 2.

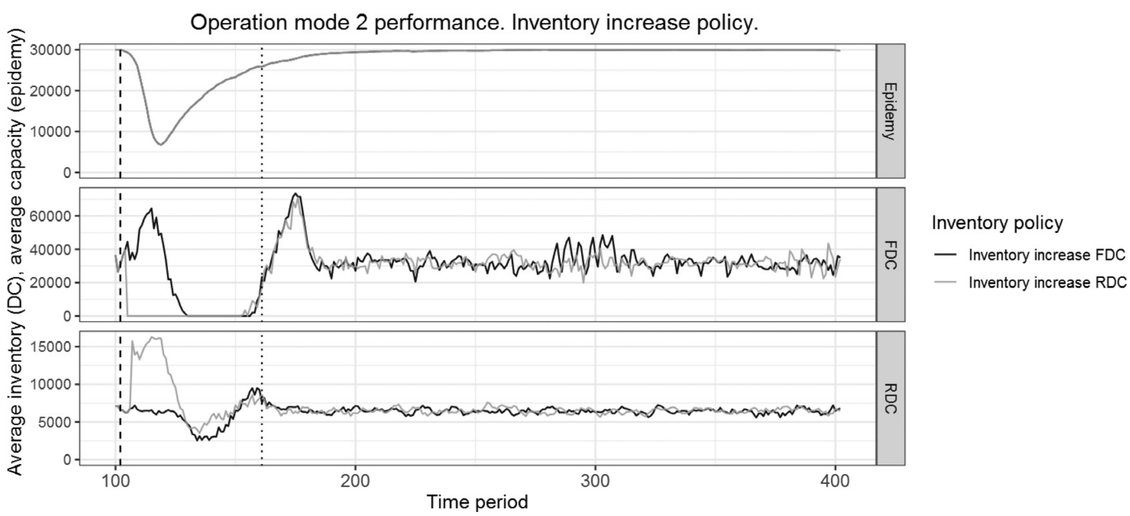

Fig. 8. Pandemic Impacts on SC Capacity and Inventory (Mode 2) when Inventory Is Increased at a Single Echelon (RDC or FDC).

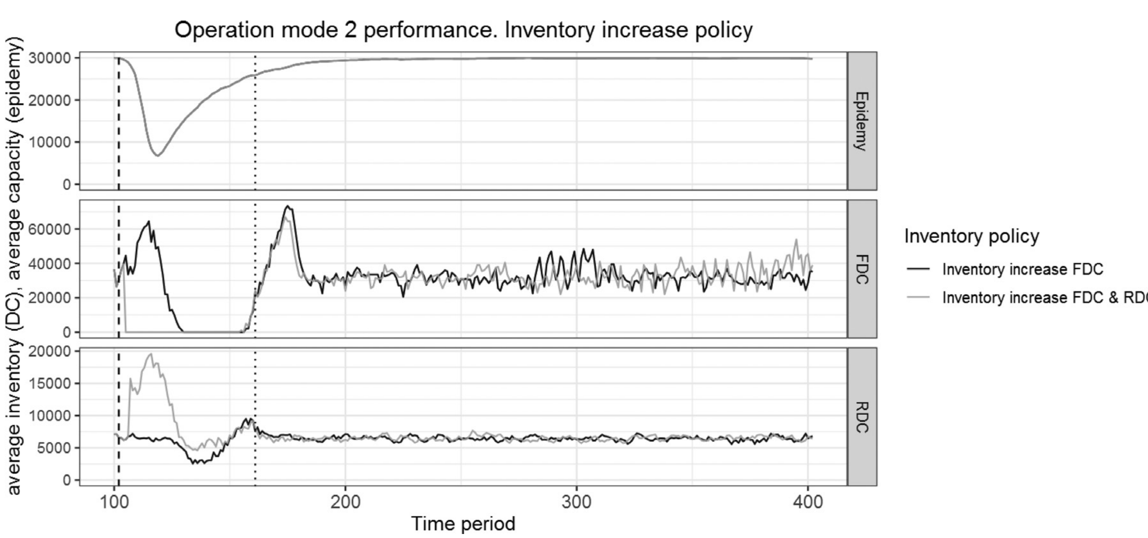

Fig. 9. Pandemic Impacts on SC Capacity and Inventory (Mode 2) when Inventory Is Increased at Two Echelons (Both RDC and FDC).

Table 3
Comparison of Efficiency and Responsiveness Performance Measures (Average for 15 Replications).

Configuration	Total Costs	Service Level	Out-of-Stock Costs	Wastage Costs
Disruption Profile I				
Mode 0 / no system reset	315,751,116	92.58%	16,517,333	3,293
Mode 0 / system reset	314,210,012	92.20%	17,351,333	329
Mode 1 / no system reset	323,844,327	91.36%	18,710,000	98,837
Mode 1 / system reset	320,729,054	90.69%	20,194,000	-
Mode 2 / no system reset	246,445,800	93.82%	13,508,667	133,606
Mode 2 / system reset	245,398,624	93.57%	14,077,333	42,418
Disruption Profile II				
Mode 0 / no quarantine	308,580,088	98.81%	2,625,333	198
Mode 0 / quarantine	305,753,576	99.92%	150,000	0
Mode 1 / no quarantine	311,456,605	98.58%	3,028,667	11,399
Mode 1 quarantine	308,284,619	99.66%	647,333	0
Mode 2 / no quarantine	233,508,078	99.20%	1,740,000	14,614
Mode 2 / quarantine	232,906,075	100.00%	0	490
Mode 2 / no quarantine and RDC stock increase	234,022,944	99.40%	1,330,667	35,170
Mode 2 / no quarantine and FDC stock increase	233,028,137	99.54%	976,667	15,275

Table 4
Statistical tests.

Configuration	Shapiro test W	Shapiro test p-value	Wilcoxon signed rank exact test V	Wilcoxon signed rank exact test p-value	Paired t-test t	Paired t-test df	Paired t-test p-value
Disruption Profile I							
Mode 0 / no system reset/system reset	0.82663	0.008247	120	6.10E-05			
Mode 1 / no system reset/system reset	0.94978	0.5211			6.46	14	1.51E-05
Mode 2 / no system reset/system reset	0.92315	0.2152			3.00	14	0.01
Disruption Profile II							
Mode 0 / no quarantine/quarantine	0.97529	0.9272			8.23	14	9.83E-07
Mode 1 / no quarantine/quarantine	0.92314	0.2151			6.81	14	8.47E-06
Mode 2 / no quarantine/quarantine	0.91329	0.1521			2.28	14	0.03914

4.3. Efficiency analysis

As discussed in Sections 4.1 and 4.2, the SC reacts differently to different disruption profiles and structural designs. In Table 3, we illustrate the impact of these reactions on SC performance.

The respective performance indicators of efficiency and responsiveness are shown in Table 3 where the performance impact is higher for instantaneous disruptions (i.e., lower service level and higher costs) as for pandemic disruption profiles. The performance impact can be mitigated by epidemic control measures (i.e., reduction of contact intensities); this is evident for all SC structural designs. Finally, we can observe that three-stage SC design demonstrates a lower exposure to pandemic disruptions than the two-stage system.

4.4. Sensitivity analysis

Our model combines three levels, i.e., pandemic dynamics, supply chain design, and operational production-inventory control policies which is not often seen jointly in literature [49,93]. In this setting, even a relatively small number of nodes in the network can yield complex behaviors at the operational level. In the literature we find that consideration of large-scale networks makes it difficult to examine operational policy dynamics in detail (e.g., [12]), while a detailed consideration at the operational level frequently leads to the necessity of considering a small-size network (e.g., [94,71,83]). Our study focuses on main operational dynamics and, hence, a set of additional sensitivity analyses have been conducted that are described in this section.

To test the stability of the model we performed additional statistical tests in R 4.1.0 for 15 replications of simulation experiments shown in Figs. 4–9 for default parameter values from Tables 3 and 4.

The Shapiro test was used for normality check, then all replications were compared with paired t-tests or Wilcoxon signed rank exact test. The cost level difference by applying recovery policy is statistically significant. We did not test stock increase measures because of their limited effect on the system's total costs. Subsequently, we conducted model sensitivity analysis to find out system response for both disruption profiles Figs. 10–12. demonstrate the results.

First, we performed sensitivity analysis regarding efficiency performance and the use of order reset recovery policy in disruption profile I. In Fig. 10 we can observe that the use of order reset policy yields lower total SC costs in all three operation modes (i.e., for all three SC designs and associated sourcing strategies). The lowest cost is observed in the mode which corresponds to our simulation results presented in Table 3.

Second, we analysed sensitivity regarding efficiency performance and the use of pandemic control measures in disruption profile II (Fig. 11). In Fig. 11 we can observe that the use of quarantine measures leads to lower total SC costs in all three operation modes (i.e., for all three SC designs and associated sourcing strategies). The lowest cost is observed in the mode 2 (i.e., the three-echelon SC design) which corresponds to our simulation results presented in Table 3. This also verifies the dynamic behaviors shown in Figs. 6–9 when the pandemic dynamics with and without lockdown and quarantine measures yields different inventory and capacity dynamics leading to lower total costs in case with the use of pandemic control measures.

Third, sensitivity of efficiency to the use of the stock increase recovery policy in disruption profile II was analysed (Fig. 12) which also confirms our findings deduced from analysis of Figs. 7–9.

Fourth, we detailed the sensitivity analysis toward different components of the total SC efficiency, i.e., out-of-stock and wastage costs (compare with Table 3 and see Fig. 13).

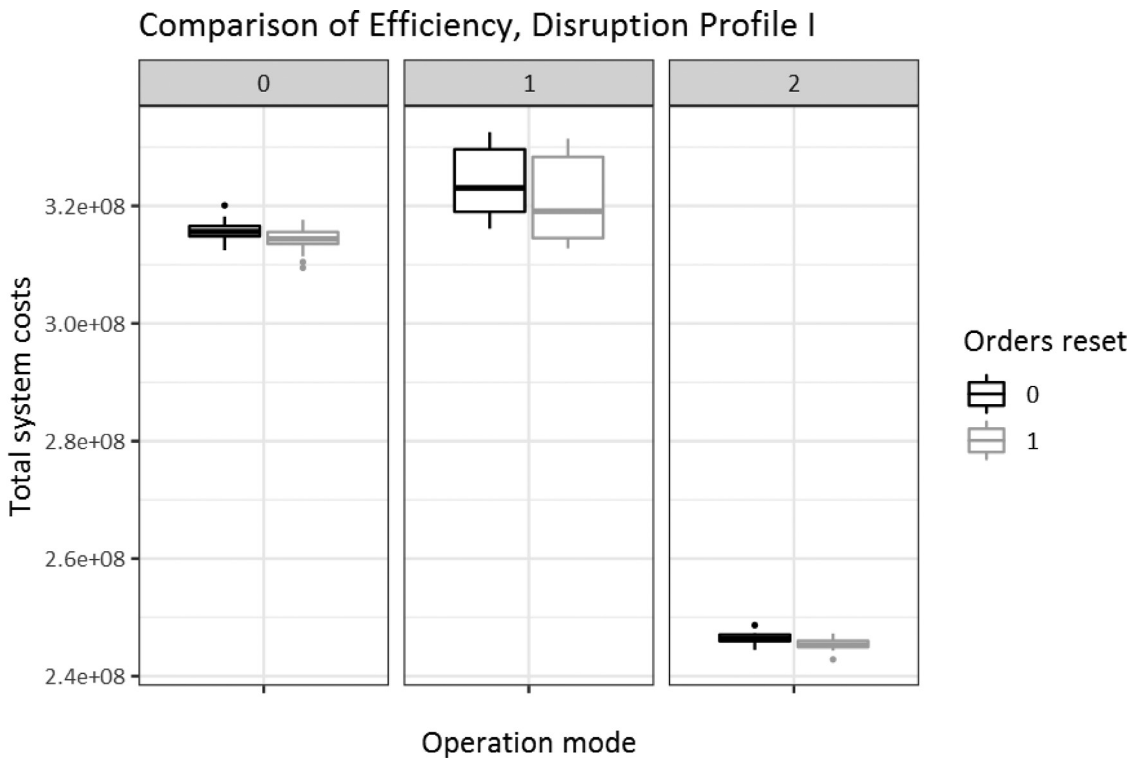

Fig. 10. Sensitivity of efficiency performance to the use (1) or non-use (0) of order reset recovery policy in disruption profile I.

Fig. 11. Sensitivity of efficiency to the use of the pandemic control measures (true) and non-use of pandemic control measures (false) in disruption profile II.

Fig. 13 demonstrates the sensitivity analysis results of our model behavior based on variation of demand for disruption profile I and contact rate for disruption profile II and their impact on out-of-stock and wastage costs. The effect of 50% capacity shortage (disruption profile I) is evident for out-of-stock dynamics – there is a certain point at which lack of stock leads to penalties. Operation mode # 2 mitigates this effect better because of higher inventory level and additional stock buffer at FDC. Wastage level dynamics due to perishable products has more complex behavior: starting from the demand level of 2000 units consumption increase outweighs wastage risks caused by the ripple effect and uncertainty. Two-stage SC configuration is more robust to surges in demand.

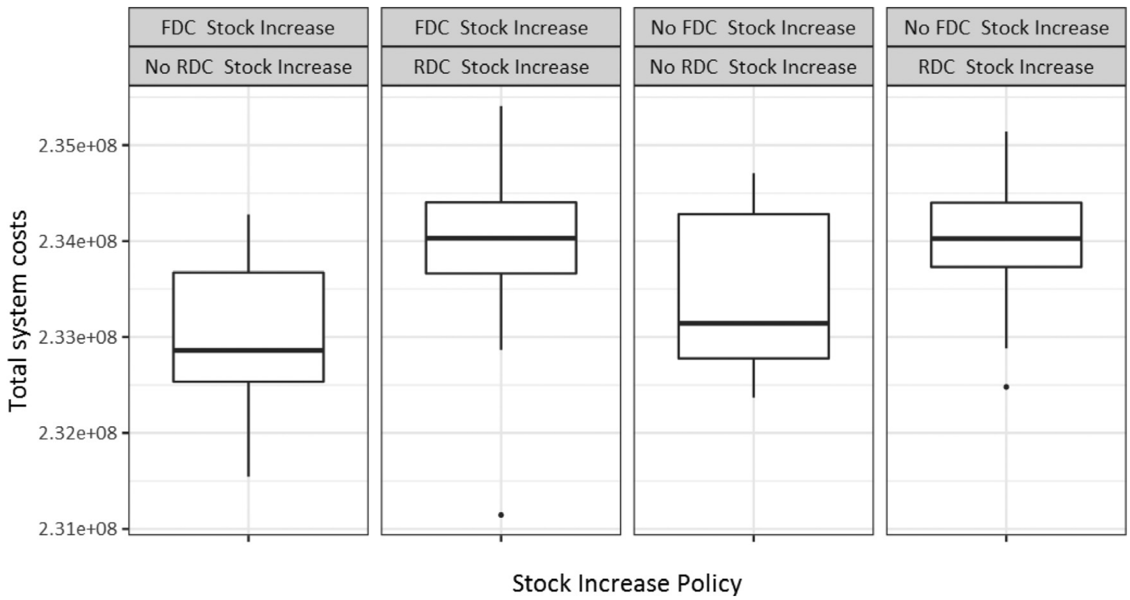

Fig. 12. Sensitivity of efficiency to the use of the stock increase recovery policy in profile II.

In case of disruption profile II, the main system stressor is contact rate and associated infection dynamics stemming from quarantine measures. In summary, the results shown in Figs. 10–13 confirm sensitivity of our model to both epidemic dynamics control and recovery policies.

5. Discussion

In this article, we investigated the exposure of different network design structures to the impact of the pandemic and how these impacts can be mediated by adaptive operational reactive decisions in anticipation of and during the pandemic. In generalized terms, we contribute to the understanding of the impacts of preparedness and recovery decisions in anticipation of and during the COVID-19 pandemic on supply chain operations and performance. We detail the discussion on the generalized effects observed in our study in this section.

5.1. Modeling and conceptual insights

The COVID-19 pandemic has offered a new resilience management context for firms. This new context has been considered in recent SC risk management literature, which is evidence of attempts to define a new theoretical lens that overarches the existing resilience theory motivated by the COVID-19 pandemic [56]. Ivanov [45] and Ivanov and Dolgui [58] proposed to conceptualize the notion of SC viability for the pandemic disruptions echoed by Lotfi et al. [95], Wang and Yao [96], Ruel et al. [97] and Feizabadi et al. [98].

In the generalized terms, the pandemic disruptions are specific and can be characterized by some major aspects. First, long-term existence of disruption and its dynamic scaling should be considered. Second, there are multiple simultaneous effects in the supply chains such as simultaneous disruptions at different echelons and simultaneous propagation of the virus and the supply chain disruptions. Third, recovery actions are deployed in the presence of disruption dynamics. Fourth, the pandemic disruption begins gradually and allows some time to make decisions on SC fortification before the onset of the pandemic (e.g., by prepositioning extra inventory). All of these features make the pandemic disruption very specific and different from instantaneous disruptions, which were most often studied in pre–COVID-19 literature on SC resilience. Unlike that of instantaneous disruptions, the pandemic profile is characterized by dynamics of degradation and recovery rather than by immediate reactions to short-term shocks to SCs, as in the case of natural disasters.

In our simulations, we analyzed both singular-event disruptions and pandemic profiles to identify similarities and differences in SC reactions. In addition, the analysis of instantaneous disruptions helped us validate the simulation model and process control algorithms for pandemic control because we used results that had been confirmed in the existing studies on SC resilience and extended them toward the analysis of the post-recovery stage. We examined SC reactions to disruptions for two-stage and three-stage network designs because these reactions might be different depending on the number of echelons in the SC. At the process level, we examined and assessed for efficiency and responsiveness (measured by fill rate) of two reactive adaptation strategies: (a) a "system reset" (e.g., cancellation of all orders in the planning algorithm at the end of disruption and when capacity is recovered) and (b) building an excess inventory at the beginning of an epidemic outbreak, with regard to the pandemic impact on SC performance measured by cost efficiency and fill rate. We considered SC recovery happening in two different settings: (a) a quick capacity decrease with a quick recovery and (b) a gradual capacity decrease with a gradual recovery (the latter is characteristic of the pandemic disruption).

We learned several generalized effects. For example we observed a system inertia, which stems from a complex SC planning algorithm for several time periods, is encountered in both cases and leads to an excess stock after a disruption is eliminated. Next, we observed that a reset of the process-planning algorithm at the time that the disruption is over is an efficient approach for a quick recovery. This observation is most relevant for the situations in which the system has not lost its full capacity and some capacity still exists to serve the incoming orders.

Many of our findings show that the number of echelons in the SC has a crucial influence on the network exposure to disruptions. The efficiency of the system reset is much lower in the three-echelon setting (i.e., mode 2) as compared to the two-echelon design (e.g., direct shipments). This lower efficiency can be seen as a consequence of the pull system of inventory replenishment: the inventory deficit at three-echelon SCs is multiplied, which leads to the backward propagation (i.e., backward ripple effect; [99,50]) of

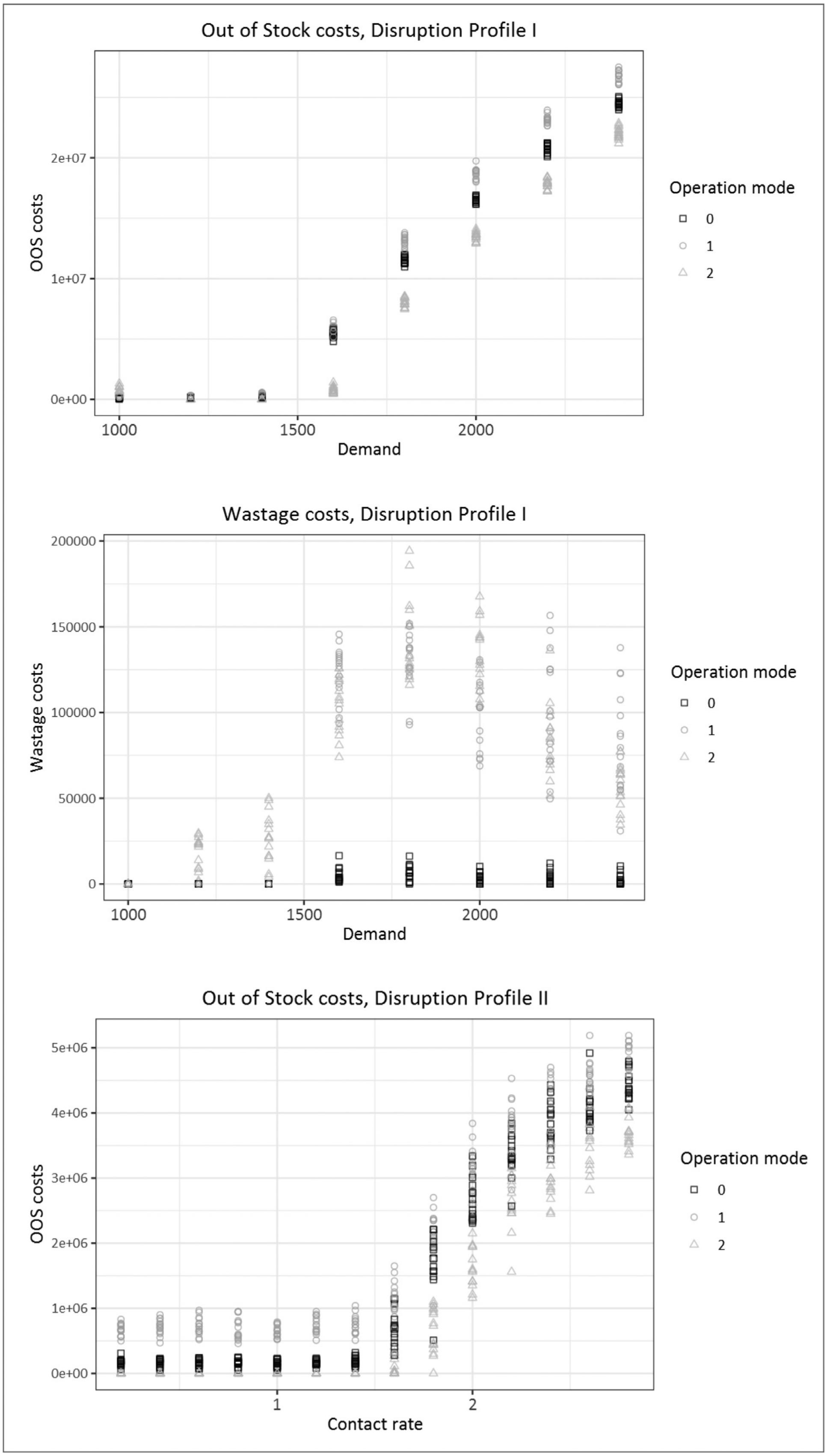

Fig. 13. Detailed costs analysis in sensitivity experiments.

the excess inventory at the time of disruption elimination and capacity recovery. At the same time, three-stage SC design demonstrates a lower exposure to pandemic disruptions as the two-stage system.

5.2. Managerial implications

The results we obtained allowed us to generalize five novel major managerial implications. First, we observed that in both disruption profiles, inventory peaks (i.e., disruption tails) happen after capacity recovery and cause the destabilization of inventory dynamics. From the management point of view, this observation implies that an adaptation of a network structural design in preparation for a pandemic is more advantageous during the anticipation of a pandemic rather than during the pandemic, when other operational recovery policies are deployed. This implication suggests that managers should avoid simultaneous changes in structural and operational policies that can destabilize the production-inventory system and result in a long shortage period during the change from one SC structure to another (e.g., from three-stage to two-stage SC).

Second, our results show little difference in inventory dynamics between instantaneous and pandemic disruption profiles at the stage after capacity recovery. As such, the existing SC resilience strategies for managing instantaneous disruptions can also be used for the pandemic disruptions. Third, and counter-intuitively, we observed that performance impact in terms of service level and costs is higher for instantaneous disruptions than for pandemic disruption profiles. Most of the literature would expect a pandemic to have more severe impacts on the SCs compared with instantaneous disruptions. However, our simulations show the opposite. This result can be explained through the lens of the pandemic disruption profile that has a gradual degradation and recovery in the case of an uncontrolled epidemic propagation and is almost smoothed at some reduced capacity (about 90–95%) of normal in the case of governmental and company protection measures. One limitation in interpreting this finding is that our settings assumed the absence of severe demand shocks during the pandemic and the effectiveness of protection measures.

Fourth, our findings indicate that an inventory increase in anticipation of a pandemic does not have any negative effects on inventory dynamics during and after the pandemic. Moreover, it has a positive effect on service level during the pandemic, especially when increasing inventory at the upstream inventory holding location (i.e., at the FDC in the setting of our model).

Fifth, we observed that a system reset stabilizes inventory dynamics in instantaneous disruptions. A direct modeling of a system reset in the pandemic setting is complicated because of the absence of a disruption recovery event. However, we find that a system reset would be an efficient measure in the pandemic setting as well because our experiments confirm a similarity in inventory dynamics across different disruption profiles and structural designs.

These managerial implications allow articulating several generalized effects. First, we have observed that supply chain adaptation ahead of a pandemic is more advantageous than during the pandemic when specific operational recovery policies are deployed. As such, the role of visibility and communication with suppliers is of utmost importance for early recognition of potential shutdowns and taking appropriate measures of inventory increase. For example, as shown in Ivanov [65], AGCO corporation had established early warning and visibility system before the pandemic. Early in 2020, they “had regular discussions with Chinese vendors and responded quickly with risk assessments and searches for alternative sourcing options. AGCO was able to source/produce as many critical parts as possible in China, and all the finished goods inventory was moved to European markets, which were still operating at the time.

Second, two-stage SC systems exhibit a higher vulnerability in disruption cases. However, they are exposed to a lower system inertia and show positive effects at the recovery stage. They are also less likely to be affected by disruption tails and inventory control policy destabilization. Third, as for the reactive recovery strategies, we note that their practical application is frequently restricted by the nature of the disruption. For example, it is not always possible to create additional stock to survive through the disruption time. Surprisingly, because the pandemic disruption is severe and much more complex it allows for a higher flexibility in deploying recovery strategies. The pandemic disruption scales up gradually at the beginning of an epidemic outbreak, so the firms have time to deploy recovery strategies to mitigate the disruption impact. However, the deployment of recovery strategies can be complicated by insufficient capacities and supply due to lockdown measures.

6. Conclusions & future work

In this study, we examined the impact of management decisions on SC preparedness and recovery in anticipation of and during the long-lasting disruptions of exogenous dynamics on the operations and performance. We accomplished this examination through the development and usage of a simulation model and were motivated by a real-life practical setting of the COVID-19 pandemic. Positioning SC networks as multilayer systems and building on a real-life case of a retail company, we examined inventory dynamics and the associated performance impacts in two- and three-stage structural settings driven by an embedded pandemic model and different scenarios for pandemic dynamics (i.e., uncontrolled propagation or controlled dispersal with lockdowns).

Most centrally, we sought to understand which network design structures are more exposed to the impact of pandemic super disruptions. We explored how these impacts can be mediated by structural designs and process recovery strategies. We triangulated our analysis by integrating three dimensionalities—network structure, process adaptation, and different pandemic scenarios — as exogenous environmental dynamics. Subsequently, we proposed, evaluated, and analyzed two types of recovery strategies that a firm can leverage to reduce the negative effects of a pandemic and the associated disruptions. First, we deployed in our model a reactive strategy, which increases inventory in anticipation of a pandemic. Second, we tested the impact of a system reset at the time of capacity recovery, which is used to avoid excess inventory rippling through the network and the associated destabilization of production-inventory dynamics.

Our analysis enabled us to deduce useful managerial implications related to which structural designs are more resistant to a pandemic and what recovery strategies firms can deploy, and when, in a pandemic setting. First, we have observed that in both disruption profiles, inventory peaks (i.e., disruption tails) occur after capacity recovery, which causes the destabilization of inventory dynamics. As such, it can be useful to perform a structural change at when anticipating a pandemic rather than during the pandemic when other operational recovery policies are deployed. Simultaneous changes in structural and operational policies can destabilize production-inventory systems and create a long shortage period during the change from one SC structure to another. Second, our results show similarities in inventory dynamics in both instantaneous and pandemic disruption profiles. Third, and counterintuitively, we observed that performance impact is higher for instantaneous disruptions than for pandemic disruption profiles in terms of service level and costs, at least in the context of our study (we note that other problem and model settings could imply different outcomes in this regard). Fourth, our findings indicate that an inventory increase in anticipation of a pandemic does not have any negative effects on inventory dynamics during and after the pandemic, and it has a positive effect on service level during the pandemic.

As with any study, limitations exist because the variety of real life is unlimited, and our modeling means are limited. Our study's limitations are related to the modeling assumptions stated in Section 2 and a "classical" limitation of all simulation studies, that is, their contextual findings. We did not explicitly model transitions between structural states, which is in line with our problem. We assumed an absence of severe demand shocks during the pandemic. Finally, the peculiarity of our analysis is the perishable products, which impose additional restrictions on order quantities and target inventory levels (i.e., the maximum level of inventory in the system) because they are constrained by the shelf-life times. This setting is quite unique and might be different in the context of nonperishable products, where analytical models would be required to determine the optimal inventory level to be prepositioned in anticipation of a pandemic, which would require connecting this decision with a forecast of the pandemic's duration.

The limitations stated above offer directions for future research. An explicit modeling of structural transitions can be of interest if one element of the network structure is disrupted and results in missing structural connectivity (e.g., if a central DC in a multistage SC is disrupted, one is forced to switch to direct shipments or to shipments via alternative DCs). We did not consider severe demand shocks [10] during the pandemic. This decision is the company's sales data for 2020. Indeed, while some short-term demand fluctuations were observed in anticipation of the first lockdown, this short-term deviation does not influence the long-term inventory and demand dynamics; as such, we allow for this simplification in the model.

In pandemic modeling, it would be interesting to include varying intensities of lockdowns (e.g., a full lockdown or a partial lockdown) as well as the duration of lockdown periods (i.e., we model only a single lockdown period with epidemic control measures of a steady intensity). Developing analytical models to determine the optimal inventory level to be prepositioned in anticipation of a pandemic is an exciting research direction, along with modeling various decentralized settings that stem from different levels of risk- and profit-aversions of SC firms and entailing game-theoretical studies. Additional inventory management approaches are needed to cope with the side effects of generic inventory management approaches. Thus, ripple-effect-related stock level stabilization methods is a promising future research direction. The uncertainty inflicted by both disruption event and recovery necessitates a set of inventory management strategies that range from lean to responsive. From the generalization point of view, our insights can be of value not only in food retail SCs but also in other economic sectors such as pharmaceutics, healthcare products, and consumer goods industries that are increasingly concerned with the management of perishable products' inventory under disruptions.

Finally, it would be very interesting to incorporate demand and pandemic forecast capability into the model. With that said, one concern about the possible extensions discussed (e.g., incorporating the pandemic forecasts using lockdown duration information) is that it might be more complex and so increase the modeling complexity and result interpretation. Different alternative methods such as robust optimization, game theory, chaos theory, Bayesian networks could be used to enhance the results of our study. In addition, uncertainty modeling by robust (conic) multivariate adaptive regression splines (R(C)MARS) methods [100] can be considered in light of further investigations of the problem coined and examined in our study. Efforts in this direction hold promise in further enhancing our understanding of managing supply disruptions due to pandemics

CRediT authorship contribution statement

Maxim Rozhkov: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization. **Dmitry Ivanov:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Jennifer Blackhurst:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Anand Nair:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision.

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