Annals of Operations Research
https://doi.org/10.1007/s10479-022-05091-7

ORIGINAL RESEARCH

Product availability and stockpiling in times of pandemic: causes of supply chain disruptions and preventive measures in retailing

Berdymyrat Ovezmyradov[1]

Accepted: 17 November 2022

Abstract
The coronavirus pandemic in 2020 brought global supply chain disruptions for retailers responding to the increased demand of consumers for popular merchandise. There is a need to adapt the existing supply chain models to describe the disruptions and offer the potential measures that businesses and governments can take to minimize adverse effects from a retail logistics perspective. This research analyses the possible reasons for supply and demand disruptions using a mathematical model of a retail supply chain with uncertain lead times and stochastic demand of strategic consumers. The established concepts of supply chain management are applied for the model analysis: multi-period inventory policies, bullwhip effect, and strategic consumers. The impact of the pandemic outbreaks in the model is two-fold: increased lead-time uncertainty affects supply, while consumer stockpiling affects demand. Consumers' rational hoarding and irrational panic buying significantly increase retailers' costs due to higher safety stock and demand variability. The bullwhip effect further exacerbates the disruption. The research contributes to the recent literature on business response to supply chain disruptions by developing a model where both retailers and consumers decide on the order quantity and reorder point during a pandemic outbreak. Buying limits, continuous inventory review, government rationing, substitutability, and omnichannel fulfillment are the measures that can limit the damage of supply chain disruptions from stockpiling during the pandemic. Effective communication and price and availability guarantees can mitigate the negative impact of panic buying.

Keywords COVID-19 · Supply chain disruption · Omnichannel retail · Bullwhip effect · Inventory management · Simulation

✉ Berdymyrat Ovezmyradov
berdyovezmuradov@gmail.com

[1] Department of Transportation and Logistics, Transport and Telecommunication Institute, Lomonosova Iela 1, Riga 1019, Latvia

1 Introduction

Outbreaks have long been known to cause supply chain disruptions, but their severity was considered low relative to other disruption causes. COVID-19 changed that perception. The recent coronavirus pandemic has drawn the attention of policymakers towards how globalized supply chains of retailers can cope with consumers' increased demand for popular merchandise. When the outbreak of COVID-19 (hereinafter, the pandemic) happened at the beginning of 2020, even major retailers with sophisticated supply chain management were unable to cope with a surge in consumers' demand for products such as toilet paper, disinfectants, and certain foods.

From a supply chain perspective, the highly publicized shortages resulted from disruptive changes in both supply and demand. Notably, the pandemic temporarily disrupted the supply of products transported from distant locations after governments imposed restrictions on business operations and travel. Yet, the disruptive force of consumer reaction to pandemics could seemingly exceed the effect of supply disruption. In many countries, there was a public perception that consumer stockpiling was a more prominent cause of shortage than supply chain disruptions (Ipsos, 2020). An essential research question is what impact the pandemic has on the supply chain when both the demand-side and the supply-side disruptions occur. Answering the question should be supported by facts and analytical modeling. The limited literature on modeling the business impact of the pandemic mainly focuses on supply-side disruptions, while the consumer-related demand disruptions received relatively little attention.

This research addresses the urgent need for new investigations of pandemic effects on businesses by contributing to the modeling research in retail supply chain disruption that integrates stockpiling consumers. This research aims to identify the underlying reasons behind the supply chain disruptions caused by the pandemic and corresponding measures to manage post-pandemic operations. In this paper, the literature and model analysis results are discussed from both the supply and demand viewpoints, but the main focus is on the demand side of retail disruption. This paper makes a contribution by incorporating the perspective of stockpiling and demand substituting consumers in a novel model of supply chain disruption. Though firms actively adapt supply chains and governments plan to ease lockdown measures further, the negative impact of the aforementioned disruptive factors is likely to remain strong for a long time after 2020 as countries are still recovering from the pandemic outbreaks and shortages of certain goods. The findings of the presented model analysis thus can be relevant because waves of the pandemic expected to occur in the future are likely to cause recurring supply chain shocks.

This research employs a mathematical model of the retail supply chain and stockpiling consumers to explain the disruptions during the epidemic and discuss the preventive measures. In the main model, the retailer uses reorder point and order-up-to policies in multi-period inventory problems with stochastic consumer demand. The retailer adjusts ordering according to the random demand of consumers who minimize their inventory and shopping costs. Consumers consider increased shortage per unit cost during the pandemic, which could motivate hoarding based on rational expectations in case of temporal supply chain disruptions. Furthermore, strategic consumer behavior could be irrational in panic buying and related to consumption's combined psychological and psychological utility. The business objective of the retailer is the achievement of the target inventory service level. A separate subsection discusses alternative inventory policies. In the extension of the main model, the retailer considers stockout-based substitution and corresponding risk-pooling reducing the bullwhip effect. In the second model extension, the forward-looking behavior of strategic consumers is taken into account. Thus the problem of inventory management during the pandemic is investigated from the perspective of three influential models in supply chain management: newsvendor-based multi-period models of stochastic demand, risk pooling, and strategic consumers. Results indicate that a combination of increasing uncertainties in the supply and demand sides of the supply chain leads to a surge in demand after the pandemic. Demand substitution reduces the harmful effect of uncertainty. Furthermore, making a strategic consumer buy quantities that maximize only their physiological utility, desirably once in lead-time between replenishment, could effectively minimize the damage of stockpiling. Specifically, buying limits and other preventive measures are discussed as managerial implications.

The next section presents the literature review. The following two sections present the analysis of the main model and its two extensions. Numerical examples and managerial implications are discussed in the following two sections. The final section summarizes the results and suggests future research.

2 Review of literature on supply chain disruptions related to pandemic

This section covers several streams of literature relevant to the study: supply chain risks, risk pooling in the bullwhip effect, hoarding, panic buying, and disruptions during the COVID-19 pandemic.

2.1 Supply chain risks

Pandemic has long been considered low risk in supply chain management with low probability and seemingly controllable mitigation (Manuj & Mentzer, 2008). Disruptions caused by the most recent pandemic make researchers rethink the risks for global supply chains. The resulting losses for retailers could amount to $700 million in the US alone from March to April 2020 (Thomas, 2020). Despite the now evident scale of pandemic impact on supply chains, there was limited analytical research on the effects of disasters on supply chains, even less on pandemic-related disruptions in retail. However, a substantial number of publications currently exist on the topic of supply chain disruptions and resilience, and the recent papers include analysis of pandemic effects (Katsaliaki, 2021).

One of the few papers on supply disruptions caused by epidemics before the pandemic in 2020 was the review by Dasaklis et al. (2012) that focused on medical supply. Another important work by Rodrigue (2016) mainly focused on transport freight relations to the pandemic. Despite the lack of analytical research on supply chain disruptions from outbreaks, results of studies modeling disasters, in general, could apply to the case of a pandemic. The ripple effect occurring when a disruption cascades downstream and impacts the performance of the entire supply chain is relevant for pandemic times; therefore, findings of related research are relevant to the issue of business responses to COVID-19 (Dolgui & Ivanov, 2021). Operational risks due to a pandemic in global supply chains to be considered in conjunction with supply risks can be summarized as follows (Rodrigue, 2016):

- The early phases of a pandemic in the modern high-speed transportation systems facilitate the spreading outbreak at the global level;
- In the later phases, economic activities are disrupted without continuous deliveries of resources as critical supply chains can shut down;

- The velocity of highly efficient global transport could lead to the paradox of the faster outbreak spread at the worldwide level relative to the local level;
- Modern food distribution relies on low levels of perishable goods for every day and stable demand, as supermarkets typically have only several days of supply for dairy, produce, and meat, while for packaged food (pasta, canned goods, etc.), the supply is one to two weeks.

Several recent studies addressed the problem of supply chain risk and disaster relief to control the spread of COVID-19. The ripple effect in supply chains during the pandemic was simulated and visualized using the system dynamics approach (Ghadge et al., 2021). Critical facilities such as warehouses for storage of emergency supplies can be located to satisfy the varying demand caused by pandemics with the aid of a two-phase optimization framework based on the Lagrangian relaxation approach (Liu, 2021). Logistics service providers managed to stay resilient during the COVID-19 outbreak, an external shock of high impact and low probability (Herold et al., 2021). Organic and mechanistic management control enabled the management of the COVID-19 crisis (Passetti et al., 2021). Supply chain 4.0 concepts became even more relevant for resilient post-COVID-19 supply chains (Frederico, 2021). Both supply risk sources and supply network recoverability are important for supply resilience (Lorentz et al., 2021). Striking a balance between being lean and resilient became one of the most important managerial implications already during the early stages of the pandemic (Raassens et al., 2021). COVID-19 has managerial implications for alertness in scenarios of huge disruptions: there is a trade-off involving the supply chain efficiency and resources orchestration to support the resilience (Queiroz et al., 2022).

In this paper, the operational risk factors of production and transport are included in the research model as an external parameter reflected in the lead-time variability, which retailers cannot control. Such an assumption simplifies decision-making in supply chain analytic practice as is common in real business. In fact, variance and related measures were widely used to analyze supply chain risk that can be highly relevant for the research agenda during the COVI-19 pandemic (Choi, 2020a). The main model described further assumes the standard deviation for calculating the retailer's safety stock increases during the pandemic.

2.2 Bullwhip effect

The well-studied bullwhip effect in supply chain management is particularly relevant for the extension of the main model in this research. The effect involves both the supply-side and demand side of the disruptive effect: demand signal processing, rationing, batching and price variations (Lee et al., 1997). The bullwhip effect of the epidemic from higher demand variability constitutes a big problem for retailers' supply chains. Numerous authors theoretically demonstrated negative consequences of the bullwhip effect (notably Chen et al., 2000; Lee et al., 1997; Metters, 1997). Highly variable orders and inventory implies additional costs for all supply chain partners: sudden surges in demand lead to rising production and storage and labor expenses even when long-term sales remain constant.

On the other hand, few researchers, including Cachon et al. (2007) and Sucky (2009), found limited empirical support for the negative bullwhip effect in several sectors: the variability does not necessarily increase or decrease at upstream stages. The pandemic modeling results in this study will be mainly discussed from the perspective of the bullwhip effect at the business-to-customer (B2C) level rather than the business-to-business (B2B) level as was typical for previous research. Indeed, the pandemic could become a more significant problem for supply of the popular products only if the following happens on a larger scale: borders closure, shortage of drivers, ports closure, production or warehouse employees getting sick, export bans, and immigration restrictions on harvesting workers (Terazono & Evans, 2020). As already mentioned, demand-side disruptions for retailers could be a threat comparable to supply disruptions during the pandemic. Available statistics demonstrated substantially higher store traffic at major retailers at the beginning of the pandemic in the US: from up to 30% at Walmart to almost 100% at Costco (Placer Labs, 2020). However, this surge was quickly followed by a sharp decline (about 50%) in the following weeks. Though foot traffic is an imprecise measure of consumer demand due to an unidentified number of shoppers switching stores or postponing purchases before the outbreak, the variability increased during the pandemic. Following theoretical predictions in the models of Chen et al. (2000) and similar authors, the sudden change in downstream consumer demand could provoke a substantial bullwhip effect in upstream supply chain unless business partners closely coordinate their actions.

The bullwhip effect can be driven by the ripple effect brought by disruptions due to COVID-19 and the corresponding impact on supply chain performance and changes in its structure (Ivanov & Dolgui, 2021). Simulations suggest that two-stage supply chains can be more vulnerable than three-stage supply chains during the pandemic disruption, but they show better effects at the recovery stage (Rozhkov et al., 2022). The bullwhip effect in this research is discussed from the perspective of consumer stockpiling and demand substitution in a novel model of supply chain disruption.

2.3 Hoarding behavior

Consumers could stockpile and impulse buy worrying about the availability of essential products during the pandemic (Anas et al., 2022; Satish et al., 2021). Early empirical and marketing research into consumer hoarding resulting from gasoline and toilet paper shortages dates back to the 1970s (Stiff et al., 1975). Observation of such behavior took part even earlier: during World War II, American consumers hoarded clothing in scare buying, and the federal government collected fines from retailers busting price ceilings (Mower & Pedersen, 2018). Stockpiling could thus happen in product categories other than grocery and hygiene, though empirical evidence is limited. Perceived scarcity of fast fashion could accelerate in-store hoarding (Byun et al., 2012). Shou et al. (2013) provided theoretical support for the conjecture that risk-averse consumers are likely to stockpile low-price products with low consumer holding costs (implying the expected spoilage cost was low), and quota policy could be beneficial for retailer's profit. Indeed, Table 1 supports such characteristics of products in high demand during the pandemic with affordable prices and long storage time (hereinafter, popular products).

Even without a pandemic, retailers may use buying limits aiming at high, but not excessively high purchase quantities by means of two approaches: offer quantity limits (for example, allowing the price deal a maximum of two times) and unit quantity limits (for example, restricting to a maximum purchase of two units of the discounted product). The associated risk is that consumers misunderstand the limits, which leads to purchasing fewer units when one of the two restrictions is imposed on a multiple unit price promotion (Carlson, 2021).

There appeared to be fewer reports of buying limits in 2021 after being increasingly announced in 2020 soon after the pandemic outbreak. Certain limits were again introduced on specific items across the US at the beginning of 2022 due to the issues related to the omicron variant of the coronavirus, weather, the supply chain struggles and labor shortages (Tyko,

Table 1 Buying limits at selected retailers (Ziady, 2020; Daoud, 2020; Jumrisko, 2020; Salaverria, 2020; Repko, 2021)

Retailer	Country and year	Products	Limit per customer
Sainsbury	UK 2020	Toilet paper, soap, long-life milk	2
Tesco	UK 2020	All products	3
Boots	UK 2020	Hand sanitizers	2
Cole	Australia 2020	Mince, pasta, flour, dry rice, paper towels, paper tissues, and handsanitizers	2
Woolworths	US, Australia 2020	Packaged goods	2
REWE Group (including REWE and Penny)	Germany 2020	Long-life foods, canned goods, and drugstore items	Decision up to store manager
Wal-Mart	US 2020	Items in unusually high demand	Decision up to store manager
Aldi	UK 2020	One unit of toilet paper Two units for dried pasta, flour, rice, paper towels, tissues, hand sanitizer	
NTUC FairPrice	Singapore 2020	Four packs of paper products, two bags of rice, four bundles of instant noodles, $36 worth of vegetables	
Retailers*	Philippines 2020	Disinfectant alcohol, hand, sanitizers, face masks, toilet paper, local canned, sardines, instant noodles, bath soap, milk, instant coffee in sachets, mineral water and bread (limits not specified)	
COSTCO	US 2021	Toilet, paper, bottled water and cleaning supplies (limits not specified)	

**Limits had been imposed on the country's manufacturers and retailers that later asked the Department of Trade and Industry to remove the limits*

2022). While the shortage of merchandise had been the main factor in 2020, the purchase limits in 2021 could be primarily driven by delays in deliveries despite the available supply of the merchandise (Repko, 2021).

This research focuses on popular products during the pandemic, though other categories were negatively affected too. Apparel sales declined by more than half during March 2020, and already troubled American department stores were hit worst (Howland, 2020). Store traffic sharply decreased by almost 80% at major consumer electronics stores during the pandemic in the US in March (Placer Labs, 2020). However, electronics sales in Russia increased by about 20% over the same period (Матовников et al., 2020). This research does not consider product categories with fashion-like and perishable characteristics and non-essential items such as alcohol that could experience unusual demand during the pandemic.

Not all stockpiling can be attributed to immediate consumer demand. Rational consumers could shop more often and buy less per trip when price variability is high (Ho et al., 1998). The impact of resellers speculating on popular products is hard to measure. An outrageous example of stockpiling that got caught in Australia could be the tip of the iceberg: a group of shoppers bought $10 000 worth of the popular items, failed to sell them online, and then tried to get a refund from a supermarket (Siebert, 2020). Retailers need to isolate the impact of the pandemic on sales from the resale, pricing, and other numerous factors that could affect aggregated consumer demand. This research assumes that demand increases are derived directly from consumption at fixed prices, not from resellers. Thus the impact of the coronavirus could be very different depending on location and product category. Furthermore, the benefits of imposing buying limits on popular products for retailers' service levels are discussed. Such purchase regulations might eliminate hoarding, but they exacerbate supply shortages due to firms reducing orders and production. A mixed approach combining price and purchase regulation can thus mitigate the shortages when capacity becomes insufficient at the beginning of a pandemic (Li and Dong, 2021).

2.4 Panic buying

Most empirical studies on the subject of panic buying involve consumer response to natural disasters. Japan, for instance, is a suitable country to study buying behavior in conditions of living within areas prone to earthquakes, typhoons, landslides, and tsunamis. Consumers in the Tokyo area exhibited higher levels of panic buying without apparent reason, particularly in households with many family members and a middle-aged or older homemaker (Masahiro and Koichiro, 2014). Various factors in the food supply chain such as resilience: emergency planning, staff training, food supply backup, food suppliers, infrastructure, location, service providers, and insurance could define the level of organizational preparedness for panic buying (Hecht et al., 2019).

Panic buying during a pandemic is still an understudied topic. Misinformation was a serious contributing factor in the panic ensuing from the COVID-19 outbreak (Elavarasan & Pugazhendhi, 2020). Certain officials and retailers in 2020 called customers to refrain from buying unusually higher amounts of products compared to regular consumption before the pandemic, and there were even instances of public and media shaming that blamed consumers for the shortage of certain products (Daoud, 2020; Jumrisko, 2020; Taylor et al., 2020). Business, government, and media efforts to convince consumers about sufficient availability and warn about the damaging effects of panic buying for a society seemingly had limited success. In response, several supermarkets, particularly in the UK, moved toward rationing popular food and other supplies, facing increased demand during the pandemic (Table 1). Furthermore, businesses expanded shelf space, counters, and logistics capacity for popular products during the pandemic. Online retailers were not immune to panic buying either: Amazon prioritized sales of medical items for hospitals, and delivery of non-essential items (primarily by third-party sellers) was delayed (Rey, 2020). Several UK online retailers suggested temporary limits and introduced virtual queues for the most popular items (Ziady, 2020).

Importantly for this research, a distinction has to be made between the changes in the underlying demand of consumers during the pandemic. Limited empirical evidence reveals critical differences in how retailers coped with panic buying of various products during the COVID-19 outbreak (Taylor et al., 2020). First, the total consumption of toilet paper as per actual use cannot realistically increase, but consumers still purchased (estimated) 40% more by remaining at home and using fewer public facilities. Despite enough domestic supply for total consumption of toilet paper, the challenging transition from commercial to retail channels contributed to the sense of widespread shortages. Unlike toilet paper, the actual use of products such as spaghetti, flour, sugar, and dry yeast increased significantly with the changing home consumption patterns. How well retailers were able to respond depends on the presence of multichannel suppliers (insufficient responses in case of competition between foodservice and retail for pasta) and whether products could be stocked at supermarkets by suppliers (proving to be resilient in case of drinks and snacks).

2.5 Models of COVID-19 impact on global supply chain

Numbers of infections are an important part of the shortage function describing changes in the inventory management model illustrated in this paper within the simulation section. Mathematical models simulating the disease spread were widely taken into account in policymaking at different levels of responding to the pandemic in 2020 (Adam, 2020). Alternative plans were suggested to reliably contain the pandemic while mitigating economic consequences (Baveja, 2020). Already early evidence on SARS-CoV-2 responsible for the COVID-19 outbreak pointed out the characteristics capable of disrupting activities of a wide range of organizations: the infection grew exponentially, justifying the typical responses to limit the disease such as isolation, quarantine, lockdown, social distancing, screening, and testing (Kaplan, 2020; Tsiligianni et al., 2022). Unlike the previous epidemics, the COVID-19 pandemic was difficult to model and control due to its long incubation period resulting in various measures determined by outdated data (Alvarez & Kreinovich, 2020). The traditional mitigation techniques of the past pandemics were not capable of containing the COVID-19 (Abideen, 2020). For policymakers, the COVID-19 characteristics also meant there was a time to be risk-averse and a time for risk-taking during the contagion or recovery phases of the pandemic (Van Oorschot et al., 2022). Overall, operations research can be applied to address the ripple effect at five pandemic stages as per the WHO classification: anticipation, early detection, containment, control and mitigation; and elimination (Ivanov & Dolgui, 2021).

Earliest papers on the economic effects of the pandemic since 2020 were published soon after the outbreak had started. The number and speed of publications on COVID-19 by social scientists increased to the extent that concerns were raised about maintaining scientific rigor (Fowler, 2020). Among the vast number of papers already available on COVID-19, this subsection focuses on mathematical models related to supply chain disruptions.

Various well-known and emerging theories were offered to help researchers build knowledge about the COVID-19 effects on supply chains (Craighead, 2020). The complex structure of global supply chains magnifies losses due to COVID-19, and pandemic control measures such as lockdowns require coordinated efforts and support across countries (Guan et al., 2020). Each industry might require unique practical approaches to minimize disruptions caused by the pandemic. For instance, a decision support system based on specialist medical knowledge and fuzzy inference can aid demand management in the healthcare supply chain (Govindan et al., 2020). Consumers' worry about COVID-19 might lead to the failure of the static service operation so that new "bring-service-near-your-home" operations can help save the service businesses (Choi, 2020b). Simulation experiments demonstrated the timing of the closing and opening of the facilities in a multi-echelon supply chain determined the COVID-19 impact rather than disruption duration or the epidemic propagation speed (Ivanov, 2020). Reducing risks in the post-COVID-19 supply chain should balance global sourcing with local sourcing and adopt multiple sources—management needs to focus not only on costs but also on resilience (Remko, 2020). Game theory and numerical examples were used to model supply chain network disruptions in terms of workforce shortages that became a critical issue as consequences of illnesses, death, travel, and other restrictions during the pandemic (Nagurney, 2021a). The pandemic devastated global economic growth due to its impact the consumption behavior (Ajmal et al., 2021). Internationally, the performance of particular private firms during the pandemic depended on financing sources, industry sectors and location (Golubeva, 2021). Predictive analytics for policymakers forecasting COVID-19 growth rates and consumer demand involved time-series, Google trends, epidemiological, and machine-learning models based on deep-learning, nearest neighbors and clustering (Nikolopoulos, 2021). Delasay et al. (2021) linked retailers' operational changes in response to COVID-19 to the customers' shopping behavior in a model of the delivery and curbside pickup. Researchers pointed to the challenges of competition and price pressure all being reinforced in the post-COVID period for omnichannel retail as a high-transparency context (Salvetti et al., 2022). Likewise, the relationships between the responses of omnichannel retailers and consumers to the pandemic are the focus of this research; however, the presented model incorporates a wider range of variables related to inventory policies, risk pooling, and strategic consumers.

This literature review reveals a considerable number of empirical and modeling studies related to the COVID-19 effects on business as of 2022 (some of the publications are discussed further in the Discussion section of this paper). However, few academic papers integrated both supply and demand sides of the supply chain disruptions due to the pandemic. Furthermore, to the best of the author's knowledge, no detailed investigation was dedicated to demand substitution and interactions between omnichannel retailers and stockpiling consumers during the disruptions. This research fills the respective gaps.

3 Model of retail supply chain with consumer hoarding

At the most basic level of the supply chain, the following aspects of operations problems can be identified in retailers' inventory management during the pandemic: product availability, product variety, and avoidance of the bullwhip effect due to stockpiling. Within the existing literature presented in the previous section, hoarding and panic buying are often given separately as causes of disruptions. Table 2 presents the notations used in this paper.

This paper defines consumer stockpiling as purchasing above the average demand due to hoarding and panic buying behavior. Hoarding is distinguished from panic buying in the presented model as a type of stockpiling based on rational arguments for consumers to buy more than necessary for satisfying their physiological needs in a certain period given the actual circumstances of holding goods at home and ongoing product availability. Panic buying is defined in this paper as stockpiling based on less rational motives due to unlikely events that could happen shortly, such as extreme shortages or soaring prices. In the following subsection, the problem of availability due to hoarding is addressed in the main model, followed by a subsection on alternative inventory policies. The next section presents two extensions of the main model that address the issues of the bullwhip effect and panic buying.

3.1 Model setting and assumptions

The simple supply chain in this research includes a retailer that faces the stochastic demand of consumers for a popular product. The product is sold at a regular fixed price per unit, p, which does not change from period to period, even after the pandemic starts. The retailer buys the product at a fixed wholesale price, w, from external suppliers. Since the inventory can be transferred from period to period, this is a multi-period inventory problem for the retailer.

Table 2 Notations and symbols

p	Unit retail price of retailer
w	Unit wholesale price of retailer
$\boldsymbol{v}$	Unit reduced price of retailer
Q	Order quantity of retailer
R	Reorder point level in RQ inventory policy of retailer
O	Fixed ordering cost of retailer
H	Unit holding cost of retailer
M	Mean of total demand observed by retailer
J	Standard deviation of demand observed by retailer
L	Mean lead-time in periods of retailer
U	Standard deviation of lead-time of delivery to retailer
t	Phase of current period
B	Safety stock in units of inventory of retailer
Z	Safety factor to determine safety stock level of retailer
$\boldsymbol{C_{RQ}}$	Retailer's expected total cost per period
$\boldsymbol{C_{cons}}$	Individual consumer's expected total cost of consumption per cycle
β	Portion of brand-switching customers
γ	Portion of store-switching customers
$f(x)$	Probability density function (PDF) of demand
$F(x)$	Cumulative distribution function (CDF) of demand
N	Total number of sales periods in retailer's planning
ζ	Number of risk-averse consumers
μ	Individual consumer's mean consumption rate in units per period
σ	Individual consumer's standard deviation of consumption rate in units per period
u	Reservation price of strategic consumers
ψ	Percentage of consumer's purchase cost per unit of carried inventory over planning horizon
χ	Consumer;s fixed shopping cost
$\acute{E}$	Consumer;s expected number of shortages per period
η	Consumer's individual shortage cost per unit
δ	Discount of future consumption by strategic consumers
r	Consumers' perceived probability of getting a product in the future at clearance price
$L_{transport}$	Delivery lead-time in sS periods of retailer
L_{review}	Inventory review periods in sS policy of retailer
CV	Coefficients of variation of B2B orders
Θ	Bullwhip effect as ratio of the coefficients of variation of orders, upstream CV to downstream CV
ρ	Coefficient of correlation of demands
Λ	Retailer's cost of unit increase in bullwhip effect

Table 2 (continued)

n ∈{*a,b,..,i*}	Product brands
k ∈ {*1,2,..,i*}	Retail stores
ʒ	New daily cases of COVID-19 infections
$\bar{ʒ}$	Average number of cases of COVID-19 infections as of May 2020 in simulation
RQ	Notation for inventory policy with reorder point and fixed order with continuous review
sS	Notation for inventory policy with periodic review and minimum/maximum levels
I	Initial inventory in each period with sS policy of retailer
s	Minimum level of inventory with sS policy of retailer
S	Maximum up-to level of inventory with sS policy of retailer
π	Expected profit of retailer

The retailer has a reorder point and fixed order policy (hereinafter, *RQ*) in which it chooses two key decision variables that provide a reasonable target service level of inventory: order quantity, *Q*, and reorder point, *R,* that triggers the placement of a new order once the reorder point level of stock is reached. The inventory review system should be continuous, which is made possible through retailing Point-of-Sale systems. *O* is the retailer's fixed ordering cost that includes ordering and shipping and handling costs per order. *H* is holding cost per unit of inventory during one period. *M* is the mean demand in units per period, while *N* is the total number of sales periods, the retailer plans in its operations (planning horizon). Usually, *N* is assumed to be twelve months in an annual plan. *J* is the standard deviation of demand during one period. *L* is mean lead-time (in periods), and this is the time between the placement of an order by the buyer and the delivery of this order by the supplier. *U* is the standard deviation of lead-time. The choice of target service level (rather than profit maximization) and other variables in the model is supported by a simulation based on canned food data and generalizable to many firms facing supply chain disruptions due to COVI-19 (Dohmen et al., 2021).

There are three distinct periods in this model denoted: 1st, pre-pandemic (before March 2020); 2nd, the start of pandemic (during March 2020); 3rd, after the pandemic start (after March 2020). As discussed later, preliminary empirical evidence supports such approximation.

The following consumer behavior model is a simplified adaptation of the model described by Ho et al., 1998. Consumers' purchasing policy is analogous to the RQ policy of retailers, except that the objective is cost-minimization instead of target service level. Consequently, the consumer decides on optimal purchase quantity and reorder point that triggers store visits. To model consumer behavior, the following assumptions have to be made for tractability. Replenishment is instantaneous, so lead-time is negligible. External competition and store switching are not present in the main model. Consumers make only planned purchases buying a product after they run out of it at home. Consumers are homogeneous in the main model concerning the parameters mentioned above. There are ζ risk-averse consumers in the local market that periodically visit the retailer to satisfy their needs. A consumer consumes a product at a stochastic rate with a mean μ and standard deviation of σ units per period, which does not change during and even after the pandemic. Certain variability σ of the demand from each consumer is because of moderate uncertainty in consumption rate and timing of store arrival throughout a given period. The planning horizon of each consumer in which the consumption and shopping expenses are minimized lies within one replenishment cycle. Thus the total consumer demand that the retailer has to meet for each period is a sum of all individual consumer demands, so $M = \mu\ \zeta$. Therefore, the variability of consumer demand in the main model is a consequence of variable consumption and random store visits in each period, $J = \sqrt{\zeta}\ \sigma$. Each time a consumer visits a store to purchase the product, a fixed shopping cost, χ, is incurred, consisting of the travel cost of a trip and transaction cost of time spent inside a store. Costs per unit of inventory carried by consumers at household each period are defined as ψp, whereψ is the percentage of purchase cost over the planning horizon. This inventory cost percentage is assumed to be proportional to the individual time value of money and space the product occupies at household storage, and it is inverse proportionate to the average storage period of a consumed product at home before expiry. The retailer's local store serves a fixed number of consumers who reside in proximity so that their shopping and inventory costs remain constant. The consumer is willing to tolerate a temporal shortage as long as it contributes to the long-term objective of cost minimization. A consumer thus incurs individual shortage cost per unit, η, in each period the product is missing from consumption in the household. $\acute{E}$ is the expected number of shortages per period, which is based on retail inventory's service level in previous periods. The shortage cost comprises a constant value of physical disutility from non-consumption and psychological regret of not having something in stock, which strongly increases during the pandemic due to anxiety about future availability and pricing. Toilet paper is a widely publicized example of such popular products providing comfort to people in times of pandemic uncertainty (the total consumption itself is not likely to show a significant increase, as the literature review discussed). When the pandemic starts, consumer adjusts purchase quantity based on a rational belief about changing shortage cost due to heightened regret experienced after stockout. It is reasonably assumed no lockdown or other restrictions during the pandemic hampers the ability of consumers to visit the local store.

The retailer's supply chain is assumed to be capable of restoring an acceptable inventory level after a certain period of adjustment. Therefore, after the initial uncertainty about product availability, the consumers' shortage cost decreases but still does not go back to pre-pandemic levels as consumers adjust their beliefs based on the observed retailing situation. Admittedly, consumers' disutility due to shortage could be a function of various factors such as beliefs proportional to the infected population curve. It would likely be a continuous one resembling the Bass Model diffusion equation as a function of time. However, the shortage parameter is assumed to be fixed in the main model for simplicity of exposition. Thus $\eta_2 \geq \eta_3 \geq \eta_1$. This assumption is reasonable and critical for the main model.

Analysis of data at the beginning of the pandemic suggested the surge in consumer demand for the popular demand currently could be a one-time event with declining oscillation. However, researchers were aware the second wave of the pandemic could start as early as autumn 2020, repeating the earlier stockpiling shock (Placer Labs, 2020). Though average monthly sales of the popular products increased up to 20% over the comparable figures for previous periods, online sales could increase as much as 300% during a week relative to the last week (BCG, 2020; Nielsen, 2020). It is those unusual hikes in day-to-day purchases that should attract the interest in modeling panic buying. The concern about shortages seems to be the main driver of hoarding behavior among consumers. Figures 1 and 2 appear to show the empirical support for the assumptions made about the retailer and consumers in the main model.

To isolate studied effects, additional simplifying assumptions are made about the retailer and consumer. The business objective of the retailer is the target service level of inventory. Such an objective is widespread due to its ease of implementation and beneficial for achieving

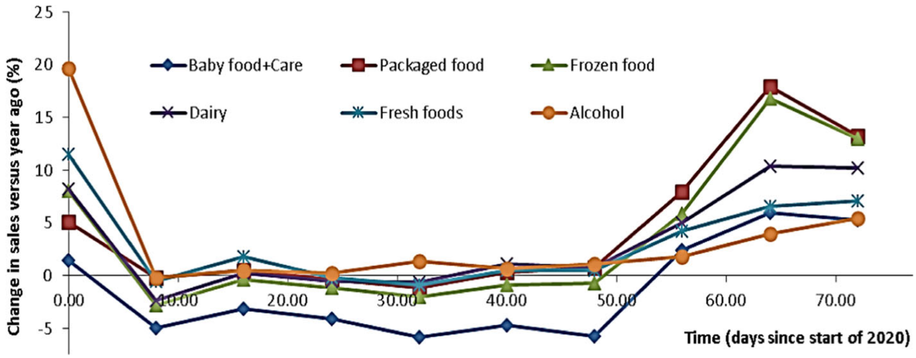

Fig. 1 Percentage change in sales of the popular products after the start of the pandemic in Italy (Source: BCG, 2020)

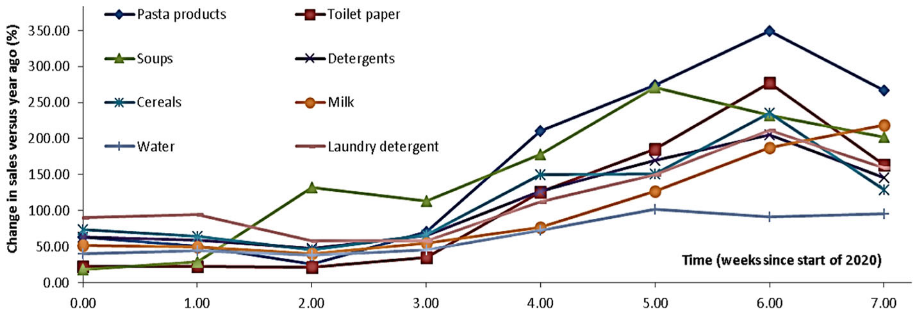

Fig. 2 The actual change in online sales of FMCG products after the start of the pandemic in Russia (Source: Nielsen, 2020)

a particular market share and customer satisfaction. Backorders are possible at unit shortage costs. Lead time to deliver a product from suppliers is positive and variable. RQ is a continuous review policy. The choice of RQ for the popular products, as indicated in Table 1, seems justified given the relatively low holding cost of such products as opposed to order-up-to and myopic newsvendor-based inventory policies that are more suitable for perishable and fashion products which have high spoilage and obsolescence rates. Suppliers impose capacity limitations. There is no variable purchasing cost for supplies, and pricing is fixed as markup. Costing parameters in the model do not change during the pandemic, which seems to be consistent with most popular products except for cases of severe disruptions, such as in the case of masks. Though it is assumed that the retailer does not change the price in the main model, a model extension later discusses the implications of the belief in future changes in pricing. One positive aspect of retail immediately after the pandemic in major countries was that prices did not seem to change significantly for most popular products (Office for National Statistics UK, 2020). There was, however, a long-term increase in global consumer price inflation due to the supply chain crisis as a result of increased maritime transport costs; it still remained below ten percentage points as of 2022 data (Grynspan, 2022).

In this study, supply disruptions are incorporated into the variability of lead-time with a normal distribution. An alternative way to model disruptions in supply disruption literature is to present them as a random process governed by the probability distribution of the number of consecutive periods with disrupted supply (Schmitt et al., 2015). The model of uncertain lead-time in this research is widely described in supply chain textbooks and easier to use. The pandemic leads to an increase in lead-time variability after the start of the pandemic. Other parameters are assumed to remain constant. Notation for all periods before the pandemic (pre-pandemic phase) is $t = 1$; for the first period right after the start of the pandemic outbreak (pandemic-start phase), it is $t = 2$; and for all the periods after (after-pandemic phase), it is $t = 3$. The duration of phase 1 in the model is assumed to be long enough for the surge in consumer demand to occur after the pandemic outbreak before deciding on adjusting inventory policy.

3.2 Analysis of demand disruptions due to stockpiling

To calculate the reorder point in RQ, safety stock and order size should be defined first. With variable lead times, safety stock to achieve the desired service level

$$B = Z\sqrt{L \cdot J^2 + M^2 \cdot U^2} \tag{1}$$

Z is a safety factor that depends on the inventory service level (probability of satisfying demand during lead-time). Safety stock could be negative (retailer would hold less inventory than average demand) if the service level is extremely low, which is excluded as an unrealistic case for real businesses. Supply disruptions in production and transportation due to the COVID-19 effect of increasing lead-time variability implies $U_2 \geq U_3 \geq U_1$. The previous sections illustrated how lead times for certain popular products could go back closer to their normal pre-pandemic levels after an initial period of adjustment. Unfortunately, data as of 2022 for the years following the outbreak show the general tendency towards lengthening the lead-times: containers typically spent 20% more time in the system for door-to-door trade, with ships and trailers stuck in congested ports (Grynspan, 2022). From the expression above, the impact of simultaneous supply disruption and a sudden increase in demand can cause a "perfect storm" for retailers after lead-time variability becomes significant due to pandemic outbreaks. The scale of such disruptions for countries with high levels of offshoring could be enormous, as in the case of US businesses that source anywhere from 3% (Nordstrom) to 60% (Best-Buy) from China (Thomas, 2020). The typical approach to finding Q in RQ policy is to use the well-known EOQ model, which gives a reasonably good approximation of the optimal order quantity for practical use (Hillier & Lieberman, 2004). The optimal purchase quantity minimizing total relevant cost in EOQ with the deterministic assumption is conveniently derived with the first-order condition as the objective function is convex.

$$Q_{rq} = \sqrt{\frac{2OMN}{H}} \tag{2}$$

The use of EOQ is nearly optimal in minimizing the retailer's long-term holding and ordering costs, C_{RQ}. Then it is straightforward to calculate reorder point with the target service level:

$$R_{RQ} = LM + B \tag{3}$$

Here, the reorder point is expressed as a sum of average demand during the lead time plus safety stock to ensure the target service level of inventory to protect against uncertainty. It is not difficult to see why maintaining the pre-pandemic levels of availability of the popular products for retailers is a challenging task: with soaring demand for items such as toilet paper, reorder points would become inadequate. To predict how consumer demand could change, a separate model has to be considered.

A rational consumer minimizes the expected total cost of consumption per cycle by balancing inventory and shopping costs in the selection of purchase quantity and reorder point before each store visit is:

$$C_{cons} = {}^{\backprime}E\frac{\eta\mu}{Q_{cons}} + \psi p\left(\frac{Q_{cons}}{2} + R_{cons} - \mu\right) + \frac{\chi\mu}{Q_{cons}} \tag{4}$$

The first term in the expression is expected shortage cost; the second term is expected inventory cost; the last term is expected shopping cost. The optimal decisions can be defined as follows.

$$Q_{cons} = \sqrt{\frac{2\mu(\chi + {}^{\backprime}E\eta)}{\psi p}} \tag{5}$$

$$F(R_{cons}) = \frac{\eta\mu}{\eta\mu + \mu\psi p} \tag{6}$$

$F(R_{cons})$ is the cumulative distribution function of individual consumer demand. The exact solution for both decision variables can be found using an iterative procedure, but an analogous approximation of EOQ planned shortages provides a reasonable heuristic for fast calculation. The result is equivalent to RQ model extensions with planned shortages and cost minimization targets. Such similarity is not surprising given analogous parameters and results in related models of consumer behavior that this study builds upon (Ho et al., 1998).

When consumers' perceived shortage cost η increases with ψp remaining constant, consumers adjust purchase quantities increasing both Q_{cons} and R_{cons} in (5) and (6). Retailer then increases R_{rq} in (3) since $M = \mu\,\zeta$ increases proportionally to η, and also R_{rq} increases in J. Opposite direction of change after the initial pandemic period with decreasing shortage cost is derived similarly. Given all the input parameters and assumptions, the following Proposition summarizes the effects of hoarding on the supply chain.

Proposition 1 *Consumer demand and retailer's reorder points for a popular product increase immediately after the start of the pandemic and then decrease but do not go back to the pre-pandemic level.*

Hoarding unnecessarily expands inventory and costs in the supply chain for both retailers and consumers even when the actual consumption rate does not show a significant increase. A couple of interesting implications of Proposition 1 should be discussed here. First, soaring consumer purchases of the popular products might render the pre-pandemic service level of inventory infeasible. At the same time, low levels of availability could hardly be acceptable for the senior management and local communities. Then the retailer could consider a scenario where each store introduces a buying limit for a certain number of substitutable products per customer. It is assumed that the business can enforce the limit long-term, implying either disciplined consumers or perfect tracking of each purchase over the entire period. If the limit can be effectively set per consumer, then order quantities for both the retailer and consumers effectively remain constant at their pre-pandemic levels. Then neither the retailer nor consumers have the motivation to change the corresponding inventory policy and shopping behavior after the pandemic. Second, if there was a longer lead-time, as in the case of consumers' shift to online shopping due to concerns about availability or social distancing, the reorder point would increase further and lead to considerable shortages at e-commerce facilities. An example of Amazon struggling to deliver on the promise of quick delivery during the pandemic even to its Prime customers is a good illustration of such a situation.

When η increases at the beginning of the pandemic with ψp remaining constant, consumer adjusts purchases increasing both Q_{cons} and R_{cons}. The retailer then reactively increases R_{RQ} since M increases proportionally to η, and, besides, R_{RQ} increases in J. Both the retailer and consumers make those adjustments based on the most recent market signals and allow a high likelihood of sustained long-term changes. When η decreases, another adjustment has to be made. This implies suboptimal purchasing and ordering policies that lead to $C_{cons2} \geq C_{cons1}$; $C_{RQ2} \geq C_{RQ,1}$. Thus the costs of pandemic disruption can be summarized by Proposition 2 as follows:

Proposition 2 *Change of buying and ordering policies during the pandemic is costly for consumers and retailers, correspondingly.*

Indeed, dramatic developments in the global supply chain management happening in the three years after the pandemic outbreak illustrate the scale of some of the changes stated by the aforementioned propositions: retail supply chain disruptions provoked the widespread shift from the just-in-time inventory to just-in-case inventory build-up (Shih, 2022). It should be noted that buying patterns for popular products could differ from the general consumption trends. In the U.S., consumers' spending initially had decreased relative to its pre-pandemic levels but showed a gradual increase afterwards (Elmassah et al., 2022). The lead-time variability will remain a serious issue as the pandemic does not appear to reverse the trend of the global sourcing any time soon (Koerber & Schiele, 2021).

3.3 Alternative inventory policies and stockpiling

Outside RQ with a continuous review, a wide range of inventory policies can be derived from a periodic review approach with maximum and minimum levels. *sS* policy is a periodic multi-period type that can be used by a retailer as a popular alternative to RQ policy described in the main model. When a significant fixed setup is present for each order and delivery schedules together with inventory review are periodic, sS policy can be preferable to RQ Total lead-time in sS would comprise of separate delivery time, $L_{transport}$, plus review period, L_{review}. Hence safety stock is larger in sS due to extra allowance for review. The optimal inventory policy with sS is to bring the inventory level up to S if the inventory falls below s level, and order nothing otherwise. It can be defined as follows:

$$Q_{ss} = \begin{cases} S - I \text{ if } I < s \\ 0 \text{ if } I \geq s \end{cases}$$

where I is the initial inventory at the beginning of each period, s is the minimum level triggering order placement, and S is the maximum up-to level derived in a manner similar to RQ with target service level objective, $S = ML + ZJ$. Retailer adjusts the policy in a range $0 < s < S$. With sS policy, the analysis gets more involved as there is no straightforward method for determining optimal s level, though the safety stock calculation is similar to the one in RQ policy. If s is made equal to S, then the inventory policy is implemented in the same manner as in the order-up-to model, which can be considered as a simplified case of sS widely used in retailing practice. When order setup cost, O, gets insignificant, order-up-to is a widespread policy in retail known for its convenience of use with the periodic review. Myopic newsvendor policy can be considered a further simplification of an order-up-to policy when inventory cannot be transferred between periods ($I = 0$) due to expiry, maintaining freshness, and similar concerns. Overall, sS and its derived policies are widely used alternatives to RQ, and they could be more relevant for perishable products with high spoilage rates rather than popular products.

The responsiveness of sS and similar policies is lower than with RQ because of the additional time, L_{review}, required for replenishment between periodic reviews. When the pandemic starts, a retailer without continuous inventory review will be slower to adjust S to maintain the target service level of fast-moving inventory. Considering the characteristics of the discussed inventory policies, the following Proposition can be formulated:

Proposition 3. *Retailers' selection of sS, order-up-to, and myopic newsvendor policies, in comparison to RQ, leads to: (i) lower availability of the popular products; (ii) higher shortage costs in a setting of increased stockout penalty.*

sS appears to be a less suitable policy for retailers than RQ during the pandemic due to a higher shortage rate with more time needed to adjust inventory. Still, sS would remain an appropriate policy in many instances, mainly when a continuous review is challenging or long enough review periods are mandated by scheduling systems.

4 Risk pooling and panic buying

As extensions of the already presented main model, the following two subsections further discuss how various costs related to the bullwhip effect and panic buying have to be incurred by the businesses and consumers in addition to those outlined in Proposition 2.

4.1 Mitigating bullwhip effect through substitutability and risk pooling

In addition to the cost of a suboptimal inventory policy due to hoarding, retailers could incur additional expenses due to higher fluctuations in the end demand. The bullwhip effect can be defined as the ratio of the coefficients of variation of orders, upstream CV to downstream CV (the alternative measure is the ratio of variances). In the case of the simple retailer-consumer supply chain in the main model: $\Theta = CV_{RQ}/CV_{cons.}$ The extra costs of order setup and irregular delivery associated with increased variability due to the bullwhip effect are assumed to linearly increase in the ratio of CV: $B_{bullwhip} = \Lambda\, \Theta$.

The value of the Λ coefficient is challenging to quantify, as previous studies show, and it is outside of the scope of this research. It is enough to assume the bullwhip effect costs are likely to be amplified during the pandemic as variability shock reverberates at the upper stages of the supply chain among suppliers. Limited empirical evidence suggests the bullwhip effect before the pandemic has been moderate or non-existent for many popular products at the upstream stages of retail supply chains across various industries (Cachon et al., 2007). It is assumed for the focus of this analysis on demand signals that suppliers do not practice variable pricing and rationing, two essential causes of bullwhip (Lee et al., 1997). It is evident from Proposition 1 how stockpiling would increase the bullwhip effect when the variability at the lowest downstream level of end consumers hikes. In a sense, the negative effect of consumer stockpiling is similar to a combination of demand signal processing and rationing with anticipation of shortages in B2B (Lee et al., 1997).

When the upstream stages in the supply chain network allow sufficient substitutability between suppliers, the harmful bullwhip effect could be reduced due to a sort of risk pooling (Sucky, 2009). One known implication of risk pooling is that stockout-based substitution of consumers facilitates inventory pooling across products and locations (Yang & Schrage, 2009). Risk pooling can help reduce safety stock (Eppen, 1979). Having substitutable products and alternative sites is more likely to reduce total inventory in a system when the following conditions are met (hereinafter, positive pooling conditions): (1) unit overstock cost is sufficiently high relative to the unit shortage cost; (2) positive skewness of the demand distribution is not strong; (3) the pooling effect is medium to high (Gerchak & Mossman, 1992; Yang & Schrage, 2009). Such conditions in a retail hold in a wide range of settings as availability policies demand low shortages. As the levels of substitution of demand increase, the demand pooling starts approaching the full pooling effect.

In this model extension, there are k stores and n substitutable products with horizontally differentiated quality (the results of the subsequent analysis would be qualitatively similar for vertically differentiated albeit with less direct effect). Substitutability here could mean different brands of the same popular product horizontally or vertically differentiated (for instance, national and store brands of coke). But it could also mean different product categories that could partially substitute one another in consumption (for instance, toilet paper and paper towels). In the case of stockout, γ portion of consumers chooses to switch to another store. Alternatively, β portion of consumers substitutes product brands or categories. It is assumed for tractability that all stores and products are the same in terms of inventory policy, costing, and substitution parameters. The demand is a random variable, while lead-time is constant and equal to one in this model extension. Demands across stores and brands are correlated with coefficient ρ. When there is no stockout-based substitution, the total safety stock in the retailing chain is determined as:

$$B_{total} = Z\sum_{1}^{k} J_j \tag{7}$$

In the case of demand substitution (store switching), the constant portion of switching consumers is assumed to be uniformly distributed among all locations. Then the total variance of retailing chain can be separated into pooled and non-pooled parts, so the total safety stock with demand substitution can be defined as follows:

$$B_{sub} = Z\left\{\sum_{1}^{k} J_i^2\left(1-\gamma_j\right) + \sqrt{\sum_{1}^{k} J_i^2\gamma_j^2 + 2\sum_{1\le i\le j\le k}^{k} \gamma_i\gamma_j Cov\left(M_i, M_j\right)}\right\} \tag{8}$$

As $\gamma \rightarrow 0$, (8) becomes equal to (7). As $\gamma \rightarrow 1$, the variance of total demand in (8) represents a sum of correlated random variables with the same variance and mean. From (7), total variance is non-increasing in γ. When the total system variance decreases, the retailer needs less safety stock to keep the same target inventory level. The ratio in expression for B decreases in the variance of the downstream stage. Consequently, both B and Q (or S) are non-increasing in γ. Results of risk pooling with product variety will be analogous if many substitutable product brands/categories are used instead of stores ($\beta > 0$). Based on the above analysis, the effect of demand substitution on inventory and variability of orders can be summarized in Proposition 4 as follows:

Proposition 4 *Assuming positive pooling conditions, safety stock and bullwhip effect in the supply chain are non-increasing in the level of store and brand switching.*

In a sense, the pooling of locations and products has different implications from classic risk-pooling models: while the number of facilities should desirably be reduced in standard settings, stockout-based substitution favors maintaining a sufficient number of locations and variety for consumers to switch between them. Risk pooling has favorable implications for competition and product variety as switching between shopping locations and brands can reduce the negative consequence of consumer hoarding. Demand substitution thus makes it easier for consumers to switch between products, stores, and even competing retail chains (further increasing β and γ). It helps reduce retailers' inventory costs while contributing to societal benefits with higher availability of popular products during the pandemic.

The risk pooling effect would be most substantial with negatively correlated demands, which is unlikely during the general change in consumer demand during the pandemic. It has other limitations. The risk pooling would be less effective with fashion-like (myopic newsvendor) settings when a very high shortage or spoilage costs prevent inventory transfer to subsequent periods, limiting pooling opportunities. Queues inside stores and unnecessary visits to locations with insufficient stock should be minimized due to social distancing. The retail policy should restrict unnecessary switching and return visits while exploiting the positive effects of risk pooling.

Though brand and store switching would positively address the average needs of consumers' physiological utility, they could also amplify panic buying behavior discussed in the following subsection due to the massive number of buyers changing stores.

4.2 Negative impact of panic buying strategic consumers

In this extension of the main model addressing panic buying, the behavior of strategic consumers follows standard models of forward-looking behavior in retail (Aviv & Pazgal, 2008; Su & Zhang, 2008; Cachon and Swinney, 2011; Swinney, 2011). In this original model setting previously applied to fashion products, there are two prices: full regular, p, and a changed (usually reduced) price, v. Consumers decide whether to buy now or later given the price difference, reservation price (equivalent to consumption utility or maximum acceptable price), u, a discount of future consumption, r, a belief about the probability of the product being in-stock later, δ. Strategic consumers have a choice of buying now and getting a consumption surplus of u_1—p, or waiting to buy later but getting uncertain utility of future consumption, $\delta\ r\ (u_2 - v)$. In the classic equilibrium with rational expectations widely applied in related supply chain models, a retailer chooses price and inventory levels maximizing the expected profit, given that homogeneous consumers purchase the product at the regular price, $(q^*, p^*) = argmax_{q,p}\pi\ (q, p)$. The alternative equilibrium where consumers wait to purchase a product at a reduced price is not feasible under the typical pricing path. Unlike in fashion supply chains, the effect of strategic consumers in pandemic times is opposite to the usual impact of waiting for future bargains.

While highly relevant for fashion retailers, the model of forward-looking behavior has been insignificant for grocers that less frequently discount prices for food and other popular products, while consumers exhibit a low discount of postponed consumption except for limited cases of items with early expiry. The perception of future shortages and price hikes experienced by panic buyers makes the model of strategic consumers relevant to retailers during the epidemic. Unlike in the fashion business with significant future discounts in both price and consumption value, the situation gets flipped here: consumers anticipate future price increases due to shortages. Therefore, the implications of the strategic consumer presence would be different for the popular products during the pandemic. However, in this research, motivating the consumer to postpone purchase is preferable because the retailer is less concerned about being profitable but instead focuses on keeping stable sales targets. In this sense, the focus of retailers on sales is beneficial for society during the pandemic. The consumer reservation price can include two components, psychological, u_{psy}, and physiological, u_{phy}, utilities of consumption so that the total is: $u = u_{psy} + u_{phy}$. Setting reasonable revenue targets instead of profitability matches the maximization of physiological utility among consumers.

First, consider pre-pandemic periods where the consumers' reservation prices, u, are uniformly distributed across time, while availability, r, and pricing, $p = v$, do not change from period to period. In such a scenario, the consumers will be split more or less uniformly between each period when a discount of future consumption, δ, is negligible (equal to one), which is likely to hold for the popular products. While u_{phy} does not change during the pandemic, u_{psy} is likely to strongly increase even though it is not essential for the actual health and living needs of consumers. Perceived shortages imply $r_2 < r_1$. During the pandemic, higher price expectations for the popular products would likely become prevalent, $v > p$. The current utility satisfying $u_1 - p$ must then be minimum or even negative for any strategic consumers to not buy now because of the spreading panic during the pandemic, even though the immediate consumption might not be preferable to future one. Since this is a less likely outcome, most purchases will be made in the current period instead of postponing purchases. The following Proposition summarizes the effect of panic buying.

Proposition 5 *Panic buying of strategic consumers based on prevalent beliefs about availability and pricing during the pandemic leads to an increase in the current period purchases at the expense of purchases in the future period.*

Coupled with increasing price expectations, the changing utility of consumption could explain widespread panic buying, which is an irrational behavior as opposed to hoarding discussed previously. Indeed, the distorted risk perception during the pandemic could trigger panic behavior among consumers (Elavarasan & Pugazhendhi, 2020). Thus retailers must somehow assuage panic buying behavior by guaranteeing that the regular price and availability remain constant. Therefore, in the preferable equilibrium during the pandemic, the retailer encourages strategic consumers to believe that pricing would stay the same or only change downward. The problem here is that rational consumers have all the reasons to believe in non-decreasing the availability of the popular products at times of supply chain disruptions on a global scale. Furthermore, rational belief will be about increasing prices because even if businesses or governments impose limits, shortages can lead to buying at higher prices from resellers.

The most effective remedy in such a situation still seems to be the buying limits. By adjusting maximum purchase for more even distribution of consumption in each period at which all consumers with the varying reservation prices are guaranteed to purchase a product at a fixed price, panic buying behavior could become irrelevant. It is acknowledged in this as well as previous models of strategic consumers that assumptions about consumer utility and equilibrium conditions are somewhat restrictive to apply in price and inventory optimization for retailers directly. Nevertheless, the modified model of forward-looking behavior of panic buyers could be valuable for a better understanding of the motives behind the panic buying aspect of consumer stockpiling.

5 Numerical examples of heterogeneous consumers and demand for the popular products

If the assumptions made in previous sections on homogeneous consumers with uniform reservation prices and consumption rates are relaxed. In that case, the findings of the main model do not change qualitatively, as numerical illustrations in the next section show. In this section,

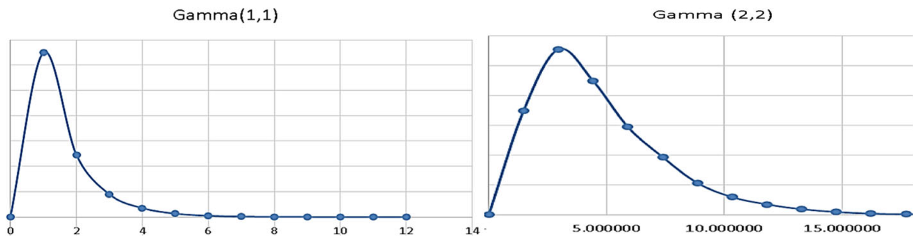

Fig. 3 Distribution of consumer shortage cost before (left) and after (right) pandemic

the theoretical and empirical justifications for parameter choice in the subsequent simulations should be discussed first. Consumers are far from being homogeneous in response to the pandemic. For instance, only 5% of Russian consumers admitted stockpiling food during the pandemic in March 2020; but 18% indicated stockpiling hygiene products (Nielsen, 2020). Senior consumers in Russia had stocked 126 consumption days of the popular products compared to 108 days for the average household (Епанчинцев, 2020). The share of consumers stockpiling food ranged from 6% in Japan to 42% in China (Ipsos, 2020).

The distribution of individual shortage cost that influences consumer demand in the simulation is assumed to follow gamma probability. Shift in demand uncertainty due to pandemics can be governed by the gamma distribution. The ability of gamma distribution to exclude negative values and approximate a wide range of demand patterns, including the most common normal and exponentially distributed ones, with varying shape and scale parameters is a significant advantage for inventory control (Burgin, 1975). Another reason for choosing gamma probability for modeling demand during a pandemic is its suitable density function with positive skewness. Its demand probability density can have a heavy right tail, which better represents a shift in consumer valuation than conventional symmetric distribution. Figure 3 describes a change in the shape and scale parameters of the gamma distribution.

In the following simulation illustrative of the main results in this research, the retailer owns a store serving one hundred local consumers. Lead-time is one week, $L = 7$, and its standard deviation is assumed to be zero before the pandemic, and afterward increasing function of global supply chain disruptions proportional to new coronavirus cases worldwide up to one week later: $U = J\text{ʒ}/\text{ƺ}$, where ʒ is new daily actual cases and ƺ is the stable average of new cases in May 2020 (Fig. 4). The target service level of inventory in RQ policy is $F(Q) = 95\%$. Other retail parameters are the order setup cost $O = 10$ and unit holding cost per period $H = 0.2$. As for consumers, inventory unit cost $\psi p = 0.1$; shopping cost $\chi = 4$, and unit shortage cost, which is an increasing function of the local, new cases (only in Europe) and assumed to be: $\eta = 10\ J\text{ʒ}/\text{ƺ}$. The consumption rate, $\mu = 1$, is one unit daily with standard deviation $\sigma = 0.1$, for all consumers. Due to random customer arrivals, the final demand from customers for the retailer's inventory policy would still appear stochastic following an approximated distribution with aggregated mean M and standard deviation J. Retailer updates inventory policy based on ten-period moving average. There is no capacity limitation in supply, so the simulation does not apply to the case of masks and similar popular products missing on shelves during the pandemic. The modeling time framework from February 30th to May 30th of 2020 is divided into three phases of equal duration into periods, each representing the distinct stages of disruption in the model. It should be noted here that all the parameters and functions in this simulation are arbitrary to a certain extent but still represent one possible scenario among many other realistic or potential ones.

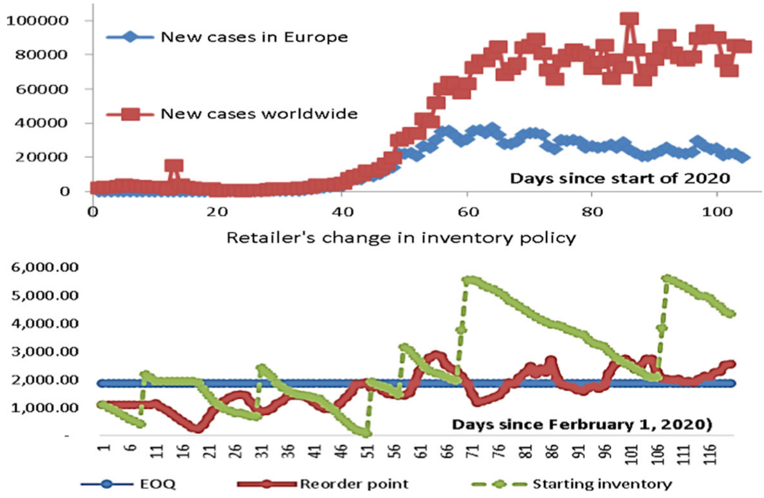

Fig. 4 Simulation result for retailer's order quantity, reorder point, and inventory level before and after the pandemic relative to new coronavirus cases (nuber of infections taken from European Centre for Disease Prevention and Control 2020)

From Fig. 4, the reorder point increases considerably at the start of the pandemic, while the order size remains fixed. Due to lead-time lag, the inventory hike is observed later after the reorder-point adjustment: the highest risk of shortages and plummeting fill rate can be anticipated at this time point.

Figure 5 summarizes the general change in supply chain performance. As consumers

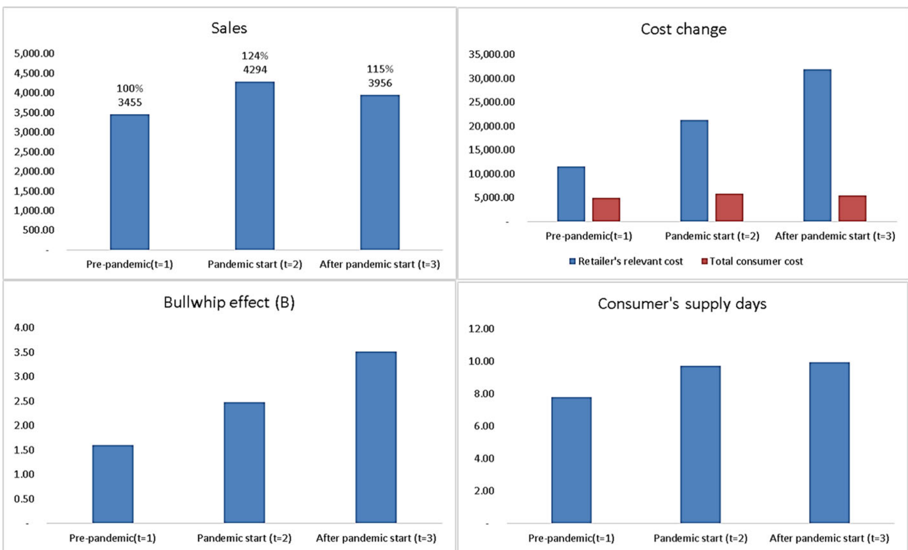

Fig. 5 Comparison of sales, costs, bullwhip effect, and days of supply (for consumer consumption) between periods

stock more at the beginning of the pandemic, but their consumption rates do not change, sales decrease after reaching a peak in the second period. While consumers experience only a slight increase in cost, the retailer incurs higher costs due to soaring safety stock. Actual costs could be higher due to the increasing bullwhip effect.

Limited empirical evidence indirectly supports the simulated patterns of changing sales and inventory: volatility of both spaghetti sales and corresponding stockouts at US supermarkets sharply increased after the COVID-19 pandemic started, but the general trend had been the highest increase immediately following the outbreak, which gradually decreased later towards the pre-pandemic levels (Taylor et al., 2020). Other cases (Figs. 1 and 2) exist that suggest similar patterns.

6 Discussion

This section separately discusses the implications of the research for retail businesses and regulators.

6.1 Implications for businesses and society

This research suggests restrictions on the number of a product in high demand that each individual can receive during the pandemic helps reduce the stockpiling effects on retail. One possible problem with buying limits could be customers immediately returning to a store to buy over the buying limit. This problem could also exacerbate the social distancing situation if a majority of consumers responded that way. A simple solution could be to track such consumers using their credit/debit and loyalty cards, but this would raise privacy issues and potential discrimination against cash-only buyers. Retailers with appropriate capabilities such as Amazon could bypass such limitations by using information technology such as AI to identify customers returning to the same store to buy over the buying limit.

Even without face recognition and other AI applications, the modern omnichannel retailers could require customers only to buy the most popular products using a buy-online-and-pickup-in-store option in advance before a store visit. This increasingly popular method of omnichannel fulfillment could also help minimize in-store time while supporting social distancing as many retailers maintain separate counters for in-store pickup. Furthermore, websites and shopping apps of omnichannel retailers or independent aggregators could help prevent unnecessary customer visits by showing real-time product availability. In theory, omnichannel retailers could switch to contactless delivery of the popular products from stores during the epidemic contributing to the societal goal of social distancing. Unfortunately, as the example of even the leading firms such as Amazon shows, the logistics capacity needs substantial expansion to meet consumer demand during the pandemic.

Another underestimated benefit of omnichannel fulfillment is increased demand substitution, as previously revealed by Ovezmyradov and Kurata (2019). Product substitution during panic buying periods can increase profitability and customer satisfaction (Tsao et al., 2019). The extension of the main model on the bullwhip effect in this research indicates brand and store switching allows reducing the harmful effects of variability during the pandemic. Real business cases exist that illustrate how a limited product variety (single brand of dry yeast available by a grocer) or difficulty of switching (commercial and consumer brands of toilet paper) exacerbates the issue of availability during the pandemic; in contrast, interchangeable products (beer, soda, and snack food) across channels allow quick response to supply chain disruption (Taylor et al., 2020). The omnichannel approach was already becoming more relevant in the post-pandemic world, where consumers are likely to keep the online shopping behaviors adopted after the outbreak (Denise, 2020). This research provides extra findings supporting investment in omnichannel fulfillment enabling mobile-responsive sites, "buy online pick up in store" services, and consistent digital experience across channels.

Switching from periodic to continuous review suggested in this research could be facilitated by rapidly developing technology such as item-level RFID tracking and AI. Closer coordination with suppliers could be required. Supply chain coordination becomes particularly important in conditions of supply-side disruptions. Cost-sharing, two-part tariff, revenue sharing, quantity discount, wholesale price, and other types of contracts are examples of supply chain coordination tools extensively analyzed in the past and recent literature (Hendalianpour et al., 2020; Liu et al., 2020; Qian, 2020). Such agreements ensuring stable pricing between suppliers and retailers could reduce the harmful effect of pricing affecting panic buying as described in the extension of the main model incorporating strategic consumers.

The main model analysis suggests a sharp increase in consumer demand at the earliest pandemic stages, so it could be tempting for retailers to invest in additional capacity. While previous studies on the bullwhip effect almost exclusively focused on supply-side variability, the current crisis is distinguished by increased demand variability of unprecedented scale, which reverberates back to upstream stages of the supply chain. Overcapacity is wasteful not only for business but also for the economy and society. Changes to the planning process and time horizon could be more effective than increasing capacity (Dohmen, 2022). In the context of the findings of this research, businesses should be careful about excessive long-term capacity in anticipation that the current surge in consumer demand is sustainable with most high-demand items. This will help avoid the costs of excess capacity and underutilization in the long term.

6.2 Implications for regulators and business-government cooperation

This section discusses further implications of the research analysis for policymakers. Politicians might compare the epidemic to warfare and consider extraordinary measures. One long forgotten measure that governments could consider for items of extreme shortage and importance, such as masks at the early stages of the pandemic, is introducing a ration stamp or card. Such rationing was widely used in the UK and US during and immediately after World War II. In other major countries such as India and the former USSR, ration cards were widely used long after the war.

Public and private funding of the promising new technology should address the priority areas as follows. Mobile applications. blockchain, 3D printing, artificial intelligence, digitalization, and related technology have become increasingly important for supply chain resilience and insights during the recent disruptions due to the pandemic (Elavarasan & Pugazhendhi, 2020; Belhadi et al., 2021; Gupta et al., 2021; Queiroz et al., 2021; Kronblad & Pregmark, 2021; Ye et al., 2022). Innovative concepts were proposed in the last-mile delivery to tackle disruptions in the supply of essential items, such as the truck-drone systems in the areas of severe infections, dysfunctioning warehouses, labour and truck driver shortages (Singh et al., 2021). Although users likely have not yet built a clear attitude towards autonomous delivery vehicles, the new technology could become essential in influencing lead times during the pandemic (Kapser, 2021).There is theoretical and empirical evidence of the importance of supply chain visibility supported by information systems during the pandemic (Yang et al., 2021). The numerical example in the previous section used an arbitrary function of disruptions and shortage costs with respect to the number of infections. Recent studies explored empirical relationships between disease transmission, social distancing and community mobility utilizing data: modeling, deep learning, historical pandemic data and mobility control (Chen et al., 2021). However, published common decision support tools and dashboards focusing on individual effects of a non-pharmaceutical intervention on health and the economy lacked visualizing the multi-criteria challenge (Tolk et al., 2021).

The use of advanced technology should not be limited to retail. Early warning systems, possibly involving big data, should help governments identify early signs of the pandemic so retailers could be informed to take corrective actions proactively. Clear labeling and announcements of buying limits and availability are essential. Firms having overstock should be ready to indicate it to potential buyers and utilize transshipments effectively to compensate for shortages in other locations.

The effectiveness of marketing campaigns to educate consumers and raise awareness of stockpiling harm cannot be overestimated. For instance, targeted ads could inform potential panic buyers via social networking that the maximum amount of house hoarding is limited by storage capacity and natural consumption. This approach could narrow the gap between real physiological and perceived psychological utilities for popular products, such as toilet paper. Again, governments could assume a leading role in facilitating such communication if businesses do not deliver products due to competition, cost, and other concerns. Notably, supermarkets, logistics providers, and suppliers were allowed to coordinate by competition watchdog in Australia in order to ensure supply at a fair price (Siebert, 2020).

Whether governments should play a more prominent role in control over consumer stockpiling is debatable yet. Particular care should be taken in regulating a purchase quantity limit in view of its pitfall (Carlson, 2021). Relative retail price regulation not exceeding a fixed ratio of the wholesale price can, at least in theory, be more effective than absolute price regulation, as it provides a production boost effect for the supply chain without stimulating consumers' hoarding (Li and Dong, 2021). Furthermore, more policy support could be provided to many companies being in the early stages of digital technologies, with low levels of data and a gap between digitization and implementation to improve supply chain performance in the COVID-19 crisis (Ye et al., 2022).

While the results of this study on preventive measures could be applicable for most products facing stockpiling during the pandemic, there seems to be no immediate fix for disruption in the supply of special goods suddenly becoming scarce such as products of hygiene (masks and ventilators) before the global supply chain adjusts. The situation with the masks was unique due to the simultaneous effect of soaring demand from medical institutions and skyrocketing consumer demand at a time when the bulk of masks have traditionally been supplied from remote locations in global supply chains, mainly China. This is where governments and businesses should cooperate to find a long-term solution Governments could provide incentives for local production of the product now deemed strategic after the outbreak. Meanwhile, retailers could introduce new innovative solutions such as multiple-use masks and matching disinfection tools.

Overall, timely communication of the following product data between businesses and consumers and regulators could play a crucial role in preventing negative consequences of stockpiling and unnecessary store traffic during a pandemic: availability, location, quality, substitution alternatives, and delivery methods.

6.3 Implications for relief supply chain, and humanitarian logistics

The importance and insufficiency of studies on supply chain disaster relief management and developing scales for resilience to supply chain disruptions have been highlighted during the COVID-19 disruption to operations experienced in a crisis-as-a-process context (Pournader et al., 2020). How suppliers and manufacturers together cope with the disruptions due to the pandemic inevitably influences the interconnected retailing, global sourcing, and relief supply chains. JD.com is a relevant example of a leading online retailer in China successfully delivering emergency supplies to individuals and hospitals in the heavily affected regions during the pandemic in collaboration with hundreds of partners across and beyond supply chains (Shen & Sun, 2021). Demand substitution is relevant for B2B settings too, and the following discussion mainly focuses on the implications of the study for partial risk pooling across upstream stages of disrupted supply chains.

Supply chain disruption studies before 2020 primarily focused on the consequences of natural and humanitarian disasters for businesses' supplies. This interest was spurred by catastrophic events such as earthquakes that disrupted the supply of critical parts in the lean supply chains of modern car makers. In response, global leaders in the efficient manufacturing, such as Toyota, the pioneer of lean manufacturing, which traditionally preferred working closely with a few key suppliers, took steps to diversify their supply chains (Shih, 2022). There are other empirical and modeling studies demonstrating the substantial costs of overly relying on just-in-time or the primary supplier during disruptions (Sanci, 2021).

The same case for redundancies in the supply chain received extra support in the theoretical and empirical literature on substitutability. Intertwined supply networks as the entirety of interconnected supply chains can help ensure resilience during coronavirus outbreaks (Ivanov & Dolgui, 2020). When supply can be disrupted by stochastic and especially deterministic demand, a decentralized system design with more facilities holding inventory could be preferable for firms (Schmitt et al., 2015). The diversity of suppliers, locations, and inventory contributes to a favourable redundancy that helps cope with post shocks in food systems (Hecht et al., 2019). There is a case study available on how substituting sourcing helped an equipment manufacturer as one of the main adaptation strategies to navigate the COVID-19 outbreak (Ivanov, 2021). Many manufacturers during the pandemic quickly switched to producing medical supplies (Elavarasan & Pugazhendhi, 2020). Globally, substitution supported the case for switching to wider use of domestic industries for capacity availability in addition to imports of essential products (Corominas, 2021). In fact, the perceived risk of COVID-19 could drive consumers to embrace locally produced food (Palau-Saumell et al., 2021). More broadly, substitution could play an important role in the process modularity of international humanitarian organizations speeding up the emergency order validation relative to the regular order validation (Salah et al., 2022).

High product diversity together with the central position in the supply chain helped improve the operational resilience of some companies during the COVID-19 pandemic (Li et al., 2022). However, the revealed benefits of substitution do not always imply increasing product variety or capacity. In fact, a prioritization with a lowered number of SKUs to reduce changeover times could be a major part of reconfiguration by a non-perishable foods manufacturer in response to the pandemic (Dohmen, 2022). Meanwhile, surplus inventory and capacity in groceries can be utilized with the cooperation between retailers and food banks during COVID-19 crisis (Penco et al., 2021). To summarize, partial risk pooling to some extent favours higher capacity and a variety of substitutable products across all supply chain stages for relief supply during the pandemic.

6.4 Alternative approaches and research

The subsection of this research is related to socio-psychological and other effects of the pandemic on consumers and retailers. The measures discussed so far are by no means exhaustive that have or could be proven to be effective. It should be noted that, for instance, recent psychological studies suggest altruistic personality curbs consumer stockpiling (Johnson, 2020). Consequently, social shaming of excessive stockpiling and reselling could be a potent incentive to act in the interest of society. Another example is a sharply rising price for each extra unit purchase of the popular product. Social media such as Twitter can also become an attractive tool for disaster management, with problems and solutions shared in real-time (Kumar et al., 2021; Singh et al., 2019). Furthermore, machine learning and tweets were used for capturing consumers' COVID-19 sentiments (Schlegelmilch et al., 2022). Attitudes towards online shopping, virtual meetings, and other teleactivities have to be studied in the context of communication issues during COVID-19 (Mouratidis & Peters, 2022). Consumer responses to COVID-19 restrictions involved complex psychological factors as evidenced by the "No Vax" and "No Green Pass" movements (Matarazzo & Diamantopoulos, 2022). Retailers can implement corporate citizenship campaigns thus reducing the consumers' fear of COVID-19and hence its negative effects such as panic buying (Arachchi et al., 2022). Meanwhile, COVID-19 crisis could have increased the demand for reliable information alongside a significant use of data provided by public organizations (Dreisiebner et al., 2021).

The need for transparent interdisciplinary studies of the COVID-19 has been driven by the concerns about an exclusive focus on one criterion resulting in new problems for others. For instance, while biomedical professionals could suggest the shutdown of facilities to minimize the contact rate, social science could raise concerns about a panic reaction with fears of attending life-saving services, and economists warned about associated financial issues (Tolk et al., 2021). Human resource management is another area of logistics within inventory control and transportation crucial for incorporation in different COVID-19 scenarios (Nagurney, 2021b). There are numerous other areas of retail supply chain management relevant for research (Schleper et al., 2021).

Acknowledging the potential benefits of more nuanced approaches to stockpiling, this research suggests that simple scientifically-based measures could be practical and easier to implement in retailing practice. At the same time, just like in other areas of social science, exaggerated results of rushed research should not lead to misleading claims during the pandemic (Fowler, 2020). While the current focus is on the pandemic, other socio-economic areas of research risk being neglected (Walker et al., 2022). Generally, more interdisciplinary research and empirical support are required to tackle the unprecedented challenges to ensure product availability during the pandemic. Some of the future work is discussed at the end of the next section.

7 Summary

The pandemic of COVID-19 in 2020 brought the urgent need to adjust not only in sectors such as health and education but also in business practices. Importantly inventory management became an urgent priority for retailers as massive shortages of essential products affected consumers and society. This research builds upon the established supply chain management theory models to analyze the consumer stockpiling during the pandemic and suggest preventive measures. The model includes a retailer and consumers that both make decisions based upon their reorder points with order quantity. Lead-time variability is assumed to reflect the supply side disruption of retail. However, the most significant impact comes from demand-side disruption from consumer stockpiling exhibiting itself in two forms: rational hoarding and speculative panic buying. Consumers first increase purchases and later re-adjust closer to the pre-pandemic level. In response, the retailer raises the reorder point. Higher safety stock and bullwhip effect resulting from the pandemic increases costs for consumers and especially retailers. However, the inventory levels return to the levels close to the pre-pandemic normal after the phase of an initial surge. A continuous inventory review policy becomes more relevant than periodic review policies. Demand substitution due to brand and store switching allows reducing the harmful (bullwhip) effect of increased variability in the supply chain. Table 3 presents a summary of potential measures against the causes of disruptions discussed in this paper.

Future work to extend this research should involve more empirical support. This exploratory research used simple models with numerous assumptions and a limited number of numerical examples so that more analytical results would be desirable. The model of a retailer in this research assumes either RQ or sS inventory policies being prevalent in retailing practice. The wide use of EOQ quantity in RQ policy provides a good approximation for optimal order size convenient to implement in practice. Furthermore, the retailer is assumed to follow a sales target objective instead of profit maximization. The assumptions mentioned above in this research are reasonable in retailing practice considering the difficulty of profit maximization methods that are primarily based on the newsvendor model. However, an extension of the study to alternative business objectives and inventory policies could be valuable for generalizing results. Finally, finding a solution for optimal buying limits could be beneficial for practitioners.

Table 3 Causes and preventive measures in supply chain disruptions caused by stockpiling during the pandemic

Causes	Factors	Countermeasures	Implementation in practice
Hoarding	Rational expectations of consumers about decreasing availability	Switch from periodic to continuous review of inventory	Shift from *sS* and similar inventory policies to reorder-point-fixed-order policy using RFID and other technologies
		Rationing by government	Ration stamps/cards for most scarce and critical items
		Higher substitution	Omnichannel fulfillment, in-store pickup
Panic buying	Irrational or speculative belief of consumers about lower availability and higher price in the future Strongly increasing psychological utility of consumption	Buying limits on each consumer purchase	Loyalty or membership card to control buying limits
		Consumer education and timely communication	Awareness campaigns and effective communication by using mass media/social networks
		Price guarantee of non-increase or decrease	By government and business
		Availability guarantee	Can be implemented only with sufficient inventory

Acknowledgements The author is thankful to two anonymous reviewers for their invaluable comments that helped to improve the manuscript immensely. This research has received funding from the European Union's Horizon 2020 Marie Skłodowska-Curie Research and Innovation Staff Exchange (MSCA RISE) Program under the grant agreement No. 870647.

References

Abideen, A. Z., Mohamad, F. B., & Hassan, M. R. (2020). Mitigation strategies to fight the COVID-19 pandemic—present, future and beyond. *Journal of Health Research, 34*, 547–562.

Adam, D. (2020). Special report: the simulations driving the world's response to COVID-19. *Nature, 580*(7802), 316–319.

Ajmal, M. M., Khan, M., & Shad, M. K. (2021). The global economic cost of coronavirus pandemic: current and future implications. *Public Administration and Policy, 24*, 290–305.

Alvarez, K., & Kreinovich, V. (2020). How can econometrics help fight the COVID-19 pandemic? *Asian Journal of Economics and Banking, 4*, 29–36.

Anas, M., Khan, M. N., Rahman, O., & Uddin, S. F. (2022). Why consumers behaved impulsively during COVID-19 pandemic? *South Asian Journal of Marketing, 3*, 7–20.

Arachchi, H. D. M., Weerasiri, R. S., & Mendis, T. (2022). Impact of perceived corporate citizenship on purchase intention: across the fear of COVID-19 during the COVID-19 pandemic. *South Asian Journal of Marketing, 3*, 38–59.

Aviv, Y., & Pazgal, A. (2008). Optimal pricing of seasonal products in the presence of forward-looking consumers. *Manufacturing & Service Operations Management, 10*(3), 339–359.

Baveja, A., Kapoor, A., & Melamed, B. (2020). Stopping Covid-19: a pandemic-management service value chain approach. *Annals of Operations Research, 289*, 173–184.

BCG. (2020). *Consumer spending tracker*. Illinois, United States: IRI Global Headquarters.

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2021). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03956-x

Burgin, T. A. (1975). The gamma distribution and inventory control. *Journal of the Operational Research Society, 26*(3), 507–525.

Byun, S. E., & Sternquist, B. (2012). Here today, gone tomorrow: Consumer reactions to perceived limited availability. *Journal of Marketing Theory and Practice, 20*(2), 223–234.

Cachon, G. P., Randall, T., & Schmidt, G. M. (2007). In search of the bullwhip effect. *Manufacturing & Service Operations Management, 9*(4), 457–479.

Carlson, J. P. (2021). A pitfall of using offer quantity limits. *The International Review of Retail, Distribution and Consumer Research, 31*(3), 358–374.

Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: the impact of forecasting, lead times, and information. *Management Science, 46*(3), 436–443.

Chen, K., Pun, C. S., & Wong, H. Y. (2021). Efficient social distancing during the COVID-19 pandemic: Integrating economic and public health considerations. *European Journal of Operational Research, 304*, 84–98.

Choi, T. M. (2020). Risk analysis in logistics systems: a research agenda during and after the COVID-19 pandemic. *Transportation Research Part E Logistics and Transportation Review, 145*, 102190.

Choi, T. M. (2020b). Innovative "bring-service-near-your-home" operations under corona-virus (COVID-19/SARS-CoV-2) outbreak: can logistics become the messiah? *Transportation Research Part e: Logistics and Transportation Review, 140*, 101961.

Corominas, A. (2021). A model for designing a procurement-inventory system as a defence against a recurring epidemic. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2021.1919779

Craighead, C. W., Ketchen, D. J., Jr., & Darby, J. L. (2020). Pandemics and supply chain management research: toward a theoretical toolbox. *Decision Sciences, 51*(4), 838–866.

Daoud, E., Mae, L., & Wadelto, B. (2020). Coles, Woolworths, Aldi: Grocery restriction limits on toilet paper, rice, pasta, milk and antibacterial wipes. *7News*.

Dasaklis, T. K., Pappis, C. P., & Rachaniotis, N. P. (2012). Epidemics control and logistics operations: a review. *International Journal of Production Economics, 139*(2), 393–410.

Delasay, M., Jain, A., & Kumar, S. (2021). Impacts of the COVID-19 Pandemic on Grocery Retail Operations: An Analytical Model. *Production and Operations Management, 31*, 2237–2255.

Denise, L. (2020). The pandemic is rewriting the rules of retail. *Harvard Business Review*.
Dohmen, A. E., Merrick, J. R., Saunders, L. W., Stank, T. T. P., & Goldsby, T. J. (2022). When preemptive risk mitigation is insufficient: the effectiveness of continuity and resilience techniques during COVID-19. *Production and Operations Management*. https://doi.org/10.1111/poms.13677
Dolgui, A., & Ivanov, D. (2021). Ripple effect and supply chain disruption management: new trends and research directions. *International Journal of Production Research, 59*, 102–109.
Dreisiebner, S., März, S., & Mandl, T. (2021). Information behavior during the Covid-19 crisis in German-speaking countries. *Journal of Documentation, 78*, 160–175.
Elavarasan, R. M., & Pugazhendhi, R. (2020). Restructured society and environment: a review on potential technological strategies to control the COVID-19 pandemic. *Science of the Total Environment, 725*, 138858.
Elmassah, S., Bacheer, S., & Hassanein, E. (2022). US consumers' confidence and responses to COVID-19 shock. *Review of Economics and Political Science*. https://doi.org/10.1108/REPS-10-2021-0098
Eppen, G. D. (1979). Effects of centralization on expected costs in a multi-location newsboy problem. *Management Science, 25*(5), 498–501.
European Centre for Disease Prevention and Control (2020). *COVID-19 Coronavirus data.* EU Open Data Portal 2020.
Епанчинцев, Е. (2020). Аналитики подсчитали, на сколько дней россияне запаслись продуктами. *РИА Новости / X5 Retail Group*.
Fowler, A. (2020). Curing Coronavirus isn't a Job for Social Scientists. *Bloomberg*.
Frederico, G. F. (2021). Towards a supply chain 4.0 on the post-COVID-19 pandemic: a conceptual and strategic discussion for more resilient supply chains. *Rajagiri Management Journal.*
Gerchak, Y., & Mossman, D. (1992). On the effect of demand randomness on inventories and costs. *Operations Research, 40*(4), 804–807.
Ghadge, A., Er, M., Ivanov, D., & Chaudhuri, A. (2021). Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2021.1987547
Golubeva, O. (2021). Firms' performance during the COVID-19 outbreak: international evidence from 13 countries. Corporate Governance: *The International Journal of Business in Society.*
Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: a case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part e: Logistics and Transportation Review, 138*, 101967.
Grynspan, R. (2022). Here's how we can resolve the global supply chain crisis. *UNCTAD*.
Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., & Gong, P. (2020). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour, 4*(6), 577–587.
Gupta, M., Shoja, A., & Mikalef, P. (2021). Toward the understanding of national culture in the success of non-pharmaceutical technological interventions in mitigating COVID-19 pandemic. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03962-z
Hecht, A. A., Biehl, E., Barnett, D. J., & Neff, R. A. (2019). Urban food supply chain resilience for crises threatening food security: a qualitative study. *Journal of the Academy of Nutrition and Dietetics, 119*(2), 211–224.
Hendalianpour, A., Hamzehlou, M., Feylizadeh, M. R., Xie, N., & Shakerizadeh, M. H. (2020). Coordination and competition in two-echelon supply chain using grey revenue-sharing contracts. *Grey Systems: Theory and Application.*
Herold, D. M., Nowicka, K., Pluta-Zaremba, A., & Kummer, S. (2021). COVID-19 and the pursuit of supply chain resilience: reactions and "lessons learned" from logistics service providers (LSPs). *Supply Chain Management: An International Journal, 26*, 702–714.
Hillier, F. S., & Lieberman, G. J. (2004). *Introduction to Operations Research*. New York: McGrawHill.
Ho, T. H., Tang, C. S., & Bell, D. R. (1998). Rational shopping behavior and the option value of variable pricing. *Management Science, 44*(12-part-2), S145–S160.
Howland, D. (2020). Apparel retailers are in trouble. *Retail Dive*.
Ipsos (2020). *Tracking coronavirus. Results from a multi-country poll.*
Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review, 136*, 101922.
Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: a conceptual and formal generalisation of four major adaptation strategies. *International Journal of Production Research, 59*(12), 3535–3552.
Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research, 58*(10), 2904–2915.

Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: managerial insights and research implications. *International Journal of Production Economics, 232*, 107921.
Johnson, M. (2020) Who Hoards? The Personality of Stockpiling Behavior. *Psychology Today.*
Jumrisko, M. (2020). Singapore Grocery Chain Starts Limiting How Much People Can Buy. *Bloomberg*.
Kaplan, E. H. (2020). OM Forum—COVID-19 scratch models to support local decisions. *Manufacturing & Service Operations Management, 22*(4), 645–655.
Kapser, S., Abdelrahman, M., & Bernecker, T. (2021). Autonomous delivery vehicles to fight the spread of Covid-19–How do men and women differ in their acceptance? *Transportation Research Part A: Policy and Practice, 148*, 183–198.
Katsaliaki, K., Galetsi, P., & Kumar, S. (2021). Supply chain disruptions and resilience: a major review and future research agenda. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03912-1
Koerber, T., & Schiele, H. (2021). Is COVID-19 a turning point in stopping global sourcing? Differentiating between declining continental and increasing transcontinental sourcing. *Journal of Global Operations and Strategic Sourcing*. https://doi.org/10.1108/JGOSS-02-2021-0018
Kronblad, C., & Pregmark, J. E. (2021). Responding to the COVID-19 crisis: the rapid turn toward digital business models. *Journal of Science and Technology Policy Management*. https://doi.org/10.1108/JSTPM-10-2020-0155
Kumar, S., Xu, C., Ghildayal, N., Chandra, C., & Yang, M. (2021). Social media effectiveness as a humanitarian response to mitigate influenza epidemic and COVID-19 pandemic. *Annals of Operations Research*. https://doi.org/10.1007/s10479-021-03955-y
Placer Labs (2020). *COVID-19 Retail Impact Tracker*. Accessed on 13.04.2020 https://www.placer.ai/covid-19/.
Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information distortion in a supply chain: the bullwhip effect. *Management Science, 43*(4), 546–558.
Li, D., & Dong, C. (2021). Government regulations to mitigate the shortage of life-saving goods in the face of a pandemic. *European Journal of Operational Research, 301*, 942–955.
Li, Y., Wang, X., Gong, T., & Wang, H. (2022). Breaking out of the pandemic: How can firms match internal competence with external resources to shape operational resilience? *Journal of Operations Management*. https://doi.org/10.1002/joom.1176
Liu, K., Liu, C., Xiang, X., & Tian, Z. (2021). Testing facility location and dynamic capacity planning for pandemics with demand uncertainty. *European Journal of Operational Research, 304*, 150–168.
Liu, Y., Wang, D. D., & Xu, Q. (2020). A supply chain coordination mechanism with suppliers' effort performance level and fairness concern. *Journal of Retailing and Consumer Services, 53*, 101950.
Lorentz, H., Laari, S., Meehan, J., Eßig, M., & Henke, M. (2021). An attention-based view of supply disruption risk management: balancing biased attentional processing for improved resilience in the COVID-19 context. *International Journal of Operations & Production Management, 41*, 152–177.
Manuj, I., & Mentzer, J. T. (2008). Global supply chain risk management strategies. *International Journal of Physical Distribution & Logistics Management, 38*, 192–223.
Matarazzo, M., & Diamantopoulos, A. (2022). Applying reactance theory to study consumer responses to COVID restrictions: a note on model specification. *International Marketing Review*. https://doi.org/10.1108/IMR-12-2021-0370
Матовников, М., Корженевский, & Н., Камротов М. (2020). Оперативная оценка потребительской активности россиян. *Лаборатория СберДанные*.
Metters, R. (1997). Quantifying the bullwhip effect in supply chains. *Journal of Operations Management, 15*(2), 89–100.
Mouratidis, K., & Peters, S. (2022). COVID-19 impact on teleactivities: role of built environment and implications for mobility. *Transportation Research Part A: Policy and Practice, 158*, 251–270.
Mower, J. M., & Pedersen, E. L. (2018). Manufacturer, retailer and consumer misbehaviour in the United States during the Second World War. *Fashion, Style & Popular Culture, 5*(1), 41–57.
Nagurney, A. (2021a). Optimization of supply chain networks with inclusion of labor: applications to COVID-19 pandemic disruptions. *International Journal of Production Economics, 235*, 108080.
Nagurney, A. (2021b). Supply chain game theory network modeling under labor constraints: applications to the Covid-19 pandemic. *European Journal of Operational Research, 293*(3), 880–891.
Nielsen (2020). *FMCG and Retail.*
Office for National Statistics UK (2020). *Coronavirus, the U.K. economy and society, faster indicators.*
Ovezmyradov, B., & Kurata, H. (2019). Effects of customer response to fashion product stockout on holding costs, order sizes, and profitability in omnichannel retailing. *International Transactions in Operational Research, 26*(1), 200–222.

Palau-Saumell, R., Matute, J., Derqui, B., & Meyer, J. H. (2021). The impact of the perceived risk of COVID-19 on consumers' attitude and behavior toward locally produced food. *British Food Journal, 123*, 281.
Passetti, E. E., Battaglia, M., Bianchi, L., & Annesi, N. (2021). Coping with the COVID-19 pandemic: the technical, moral and facilitating role of management control. *Accounting, Auditing & Accountability Journal, 34*, 1430–1444.
Penco, L., Ciacci, A., Benevolo, C., & Torre, T. (2021). Open social innovation for surplus food recovery and aid during COVID-19 crisis: the case of Fondazione Banco Alimentare Onlus. *British Food Journal*. https://doi.org/10.1108/BFJ-02-2021-0116
Pournader, M., Kach, A., & Talluri, S. (2020). A review of the existing and emerging topics in the supply chain risk management literature. *Decision Sciences, 51*(4), 867–919.
Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C., & Machado, M. C. (2022). Supply chain resilience in the UK during the coronavirus pandemic: a resource orchestration perspective. *International Journal of Production Economics, 245*, 108405.
Raassens, N., Haans, H., & Mullick, S. (2021). Surviving the hectic early phase of the COVID-19 pandemic: a qualitative study to the supply chain strategies of food service firms in times of a crisis. *The International Journal of Logistics Management*. https://doi.org/10.1108/IJLM-01-2021-0013
Remko, V. H. (2020). Research opportunities for a more resilient post-COVID-19 supply chain–closing the gap between research findings and industry practice. *International Journal of Operations & Production Management, 40*(4), 341–355.
Repko, M. (2021). *Costco brings back purchase limits on toilet paper, cleaning supplies and More*. New Jersey: CNBC.
Rey, J. (2020). Amazon is banning the sale of N95 and surgical masks to the general public. *Vox*.
Rodrigue, J. P. (2016). *The Geography of Transport Systems*. Taylor & Francis.
Rozhkov, M., Ivanov, D., Blackhurst, J., & Nair, A. (2022). Adapting supply chain operations in anticipation of and during the COVID-19 pandemic. *Omega, 110*, 102635.
Salaverria, L. (2020). *Manufacturers, retailers seek lifting of purchase limits*. Makati: Philippine Daily Inquirer.
Salvietti, G., Ziliani, C., Teller, C., Ieva, M., & Ranfagni, S. (2022). Omnichannel retailing and post-pandemic recovery: building a research agenda. *International Journal of Retail & Distribution Management, 50*, 1156–1181.
Sanci, E., Daskin, M. S., Hong, Y. C., Roesch, S., & Zhang, D. (2021). Mitigation strategies against supply disruption risk: a case study at the Ford Motor Company. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2021.1975058
Satish, K., Venkatesh, A., & Manivannan, A. S. R. (2021). Covid-19 is driving fear and greed in consumer behaviour and purchase pattern. *South Asian Journal of Marketing, 2*, 113–129.
Schlegelmilch, B. B., Sharma, K., & Garg, S. (2022). Employing machine learning for capturing COVID-19 consumer sentiments from six countries: a methodological illustration. *International Marketing Review*. https://doi.org/10.1108/IMR-06-2021-0194
Schleper, M. C., Gold, S., Trautrims, A., & Baldock, D. (2021). Pandemic-induced knowledge gaps in operations and supply chain management: COVID-19's impacts on retailing. *International Journal of Operations & Production Management, 41*, 193–205.
Schmitt, A. J., Sun, S. A., Snyder, L. V., & Shen, Z. J. M. (2015). Centralization versus decentralization: risk pooling, risk diversification, and supply chain disruptions. *Omega, 52*, 201–212.
Shen, Z. M., & Sun, Y. (2021). Strengthening supply chain resilience during COVID-19: a case study of JD.com. *Journal of Operations Management*. https://doi.org/10.1002/joom.1161
Shih, W. (2022) From Just-In-Time to Just-In-Case: Is Excess and Obsolete Next? *Forbes*.
Shou, B., Xiong, H., & Shen, X. M. (2013). Consumer panic buying and quota policy under supply disruptions. *Working paper.* Hong Kong: City University of Hong Kong.
Siebert, B. (2020). Coronavirus hoarder tries to return $10,000 worth of goods to Adelaide supermarket. *ABC Radio.*
Singh, J. P., Dwivedi, Y. K., Rana, N. P., Kumar, A., & Kapoor, K. K. (2019). Event classification and location prediction from tweets during disasters. *Annals of Operations Research, 283*(1), 737–757.
Singh, S., Kumar, R., Panchal, R., & Tiwari, M. K. (2021). Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research, 59*(7), 1993–2008.
Stiff, R., Johnson, K., & Tourk, K. A. (1975). Scarcity and hoarding: economic and social explanations and marketing implications. *ACR North American Advances*.
Su, X., & Zhang, F. (2008). Strategic customer behavior, commitment, and supply chain performance. *Management Science, 54*(10), 1759–1773.
Sucky, E. (2009). The bullwhip effect in supply chains—an overestimated problem? *International Journal of Production Economics, 118*(1), 311–322.

Swinney, R. (2011). Selling to strategic consumers when product value is uncertain: the value of matching supply and demand. *Management Science, 57*(10), 1737–1751.
Taylor, D., Pritchard, A., Duhan, D., & Mishra, S. (2020). What's behind the empty grocery shelves. *Supply Chain Management Review*, 1–4.
Terazono, E., & Evans, J. (2020). How coronavirus is affecting pasta's complex supply chain. *Financial Times.*
Thomas, L. (2020). Coronavirus wreaks havoc on retail supply chains globally, even as China's factories come back online. *CNBC*.
Tolk, A., Harper, A., & Mustafee, N. (2021). Hybrid models as transdisciplinary research enablers. *European Journal of Operational Research, 291*(3), 1075–1090.
Tsao, Y. C., Raj, P., & Raj, P. V. (2019). Product substitution with customer segmentation under panic buying behavior. *Scientia Iranica*. https://doi.org/10.24200/sci.2019.5099.1093
Tsiligianni, C., Tsiligiannis, A., & Tsiliyannis, C. (2022). A stochastic inventory model of COVID-19 and robust, real-time identification of carriers at large and infection rate via asymptotic laws. *European Journal of Operational Research, 304*, 42–56.
Tyko, K. (2022). Grocery stores still have empty shelves amid supply chain disruptions,omicron and winter storms. *USA Today.*
Van Oorschot, K. E., Van Wassenhove, L. N., & Jahre, M. (2022). Collaboration–competition dilemma in flattening the COVID-19 curve. *Production and Operations Management*. https://doi.org/10.1111/poms.13709
Walker, J., Brewster, C., Fontinha, R., Haak-Saheem, W., Benigni, S., Lamperti, F., & Ribaudo, D. (2022). The unintended consequences of the pandemic on non-pandemic research activities. *Research Policy, 51*(1), 104369.
Yang, H., & Schrage, L. (2009). Conditions that cause risk pooling to increase inventory. *European Journal of Operational Research, 192*(3), 837–851.
Yang, J., Xie, H., Yu, G., & Liu, M. (2021). Antecedents and consequences of supply chain risk management capabilities: an investigation in the post-coronavirus crisis. *International Journal of Production Research, 59*(5), 1573–1585.
Ye, F., Liu, K., Li, L., Lai, K. H., Zhan, Y., & Kumar, A. (2022). Digital supply chain management in the COVID-19 crisis: an asset orchestration perspective. *International Journal of Production Economics, 245*, 108396.
Ziady, H. (2020). Panic buying is forcing supermarkets to ration food and other supplies. *CNN Business.*