### Title
Assessing E-retailer’s Resilience During the COVID-19 Pandemic




### Authors
Jaller, Miguel
Pahwa, Anmol



### Publication Date
2022-07-01

### DOI
10.7922/G20G3HGR

RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

# Assessing E-retailers' Resilience During the COVID-19 Pandemic

Miguel Jaller, Ph.D., Associate Professor, Civil and Environmental Engineering, University of California, Davis
Anmol Pahwa, Ph.D. Student, Civil and Environmental Engineering, University of California, Davis

July 2022

UC DAVIS Institute of Transportation Studies

Report No.: UC-ITS-2021-06 | DOI: 10.7922/G20G3HGR

# Technical Report Documentation Page

| 1. Report No. | 2. Government Accession No. | 3. Recipient's Catalog No. |
|---|---|---|
| UC-ITS-2021-06 | N/A | N/A |

| | |
|---|---|
| **4. Title and Subtitle**<br>Assessing E-retailer's Resilience During the COVID-19 Pandemic | **5. Report Date**<br>July 2022<br>**6. Performing Organization Code**<br>ITS-Davis |
| **7. Author(s)**<br>Miguel Jaller, https://orcid.org/0000-0003-4053-750X<br>Anmol Pahwa, https://orcid.org/0000-0002-9431-3168 | **8. Performing Organization Report No.**<br>UCD-ITS-RR-22-74 |
| **9. Performing Organization Name and Address**<br>Institute of Transportation Studies, Davis<br>1605 Tilia Street<br>Davis, CA 95616 | **10. Work Unit No.**<br>N/A<br>**11. Contract or Grant No.**<br>UC-ITS-2021-06 |
| **12. Sponsoring Agency Name and Address**<br>The University of California Institute of Transportation Studies<br>www.ucits.org | **13. Type of Report and Period Covered**<br>Final Research Report (July 2020 — March 2022)<br>**14. Sponsoring Agency Code**<br>UC ITS |

**15. Supplementary Notes**
DOI:10.7922/G20G3HGR


**16. Abstract**
The COVID-19 pandemic led to a significant breakdown of the traditional retail sector, resulting in a substantial surge in e-commerce demand for the delivery of essential goods. The e-retailers coped with this surge in demand, albeit while operating at a much lower level of service than usual, by outsourcing part of their operations through: crowdsourced delivery fleets, alternative pickup/delivery locations, 3rd party logistics service providers, etc. Given e-retailers' role in the supply of essential goods, the pandemic raised concerns pertaining to e-retailers' ability to maintain and efficiently restore level of service in similar market disruptions. This study assesses the resilience of last-mile distribution operations under disruptions, by integrating a continuous approximation–based last-mile distribution model; the resilience triangle concept; and the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) resilience framework. The resulting integrated tool, the R4 Resilience Triangle Framework, is a novel performance-based qualitative-cum-quantitative domain-agnostic framework (where "domain" means "discipline," such as engineering, economics, etc.). Through a set of empirical analyses, this study highlights the opportunities and challenges of different distribution/outsourcing strategies to cope with disruption. For example, the study analyzed the use of an independent crowdsourced fleet (flexible service contingent on driver availability); the use of collection-point pickup (unconstrained downstream capacity contingent on customer willingness to self-collect); and integration with a logistics service provider (reliable service with high distribution costs). Overall, the e-retailers must create a suitable platform to ensure reliable crowdsourced deliveries, position sufficient collection-points to ensure customer willingness to self-collect, and negotiate contracts with several logistics service providers to ensure adequate backup distribution.


| | |
|---|---|
| **17. Key Words**<br>E-commerce, COVID-19, pickup and delivery services, third party logistics providers, disaster resilience, demand, last mile, empirical methods, | **18. Distribution Statement**<br>No restrictions. |

| 19. Security Classification (of this report) | 20. Security Classification (of this page) | 21. No. of Pages | 22. Price |
|---|---|---|---|
| Unclassified | Unclassified | 56 | N/A |

Form Dot F 1700.7 (8-72) Reproduction of completed page authorized

## About the UC Institute of Transportation Studies

The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

## Acknowledgments

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California through the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project. The authors would also like to thank Sarah Dennis, Ph.D. student in Civil and Environmental Engineering at UC Davis, for assistance in data curation.

## Disclaimer

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

# Assessing E-retailers' Resilience During the COVID-19 Pandemic

**Miguel Jaller, Ph.D., Associate Professor, Civil and Environmental Engineering, University of California, Davis**
**Anmol Pahwa, Ph.D. Student, Civil and Environmental Engineering, University of California, Davis**

**July 2022**

UCDAVIS Institute of Transportation Studies

Report No.: UC-ITS-2021-06 | DOI: 10.7922/G20G3HGR

# Table of Contents

# Table of Contents

# List of Tables

# List of Figures

# Glossary

| Acronym | Definition |
|---|---|
| CA | continuous approximation |
| LSP | logistics service provider |
| R4 | Robustness, Redundancy, Resourcefulness, and Rapidity [a descriptor of a resilience framework] |

# Executive Summary

# Executive Summary

In the years leading up to the COVID-19 pandemic, the retail sector had seen a steady and significant shift towards e-commerce. Yet, traditional in-store shopping continued to dominate daily consumer purchase despite the ease of online shopping. However, the onset of the COVID-19 pandemic triggered a sudden and significant shift in consumer shopping behaviors. Due to the aggressive virus containment measures that significantly inhibited public movement, an unprecedented number of consumers, including many first-time users took to e-commerce platforms to purchase critical goods—daily essentials, groceries, shelf-items, medication, and health-care products. Beyond the typical B2C service, some e-retailers also witnessed demand for personal protective equipment—gowns, masks, gloves, etc. from frontline healthcare workers and hospitals. However, the COVID-19 pandemic exposed vulnerabilities of a supply-chain that is typically designed for low-cost, just-in-time delivery, capable of coping with only minor disruptions.

Considering the last-mile and the role of e-commerce distribution in ensuring delivery of essential goods, this work assesses the last-mile distribution resilience in terms of e-retailers' ability to maintain and efficiently restore level of service in the event of such a low-probability high-severity disruption. To make this assessment, we integrate the following: (i) a continuous approximation (CA)–based last-mile distribution model (*1*); (ii) the resilience triangle concept (*2*); and (iii) the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) resilience framework (*3*). Item (ii), the resilience triangle concept is a graphical representation of infrastructure function over time, whereby a disruptive event causes an immediate drop in infrastructure function that then gradually recovers over time (*2*). In sum, the resulting integrated tool that combines (ii) and (iii) above is a novel performance-based qualitative-cum-quantitative domain-agnostic framework, which we call the R4 Resilience Triangle Framework. This resilience framework quantifies the qualitative properties of resilience, i.e., robustness, redundancy, resourcefulness, and rapidity using the resilience triangle, thereby characterizing the drop in performance of the system due to the disruption. Moreover, the domain-agnostic nature of this resilience framework enables assessment of a system's response to disruption not only in the context of transportation systems, but across varying domains (i.e., disciplines, such as structural engineering, transportation engineering, or broader disciplines such as engineering or economics).

To cope with the disruption, we assume that the e-retailer outsources part of its operations via (i) a crowdsourced fleet for delivery, (ii) collection-points for customer pickup, and/or (iii) a logistics service provider (LSP) for distribution from its micro-hubs using cargo-bikes. The analyses in this study highlight the opportunities and challenges with an independent crowdsourced fleet-flexible service contingent on driver availability, with collection-point pickup (i.e., unconstrained downstream capacity contingent on customer willingness to self-collect), and with the LSP (i.e., reliable service with high distribution costs). Thus, it could be useful to establish crowdsourced delivery to cope with low severity disruption, deploy backup distribution for moderately severe disruptions, and encourage customers to self-collect packages to cope with high severity disruptions. Nonetheless, the e-retailer must carry out appropriate pre-disruption planning to create suitable platforms and incentives to ensure reliable crowdsourced delivery, position sufficient number of lockers near residential areas to ensure customer willingness to self-collect packages, and negotiate contracts with several LSPs to ensure backup last-mile distribution. Moreover, as the disruption evolves, the e-retailer must gauge availability of crowdsourced drivers, willingness of customers to self-collect packages, and the capability of the LSP to ensure functionality of its distribution channel, in order to deploy the appropriate outsourcing channel during the different phases of the disruption. And finally, as the disruption recedes, the e-retailer must re-engage strategic and tactical decision-making processes not only to restore the level of service efficiently and in a timely manner, but also to plan ahead for a different post-disruption landscape. Moreover, the e-retailer and regulatory bodies must consider equity implications for staff, workers, drivers, customers, and the communities in general, in order to ensure safe working environments, prevent job hazards, mitigate freight-related externalities, and ensure home-based accessibility to typically disadvantaged neighborhoods not only under business-as-usual conditions, but with special protocols for each phase of the disruption. Thus, consistent with other studies in the resilience literature, this study highlights the need for organizational, social, economic, and engineering units of last-mile distribution to consistently perform pre-disruption mitigation, appropriately respond during the disruption, and efficiently carry out post-disruption analysis and recovery for last-mile distribution to be resilient to disruption.

# Contents

# Introduction

The retail sector, traditionally dominated by brick-and-mortar stores, has witnessed an increasing presence of e-commerce in the past 10 years. At the turn of the 21st century, e-commerce barely accounted for 1% of total retail sales, yet by the end of the last decade (i.e., 2020), more than a tenth of all retail sales came from online channels (*4*). This steady 15% annual growth in e-commerce sales, in contrast to 4% annual growth in total retail sales in the past decade, came about due to a consistently improving online shopping experience for the consumer (cheaper shipping, expedited deliveries, free returns, etc.) and improved proximity to the market for the e-retailer (digital omnipresence). Yet, despite the ease of online shopping, the wide-range of product availability online, and the lucrative offers available on e-commerce platforms, traditional in-store shopping continued to be the dominant channel for daily purchases (*5*). However, this changed when the COVID-19 pandemic enforced a sudden and significant shift in consumer shopping behaviors (*6*).

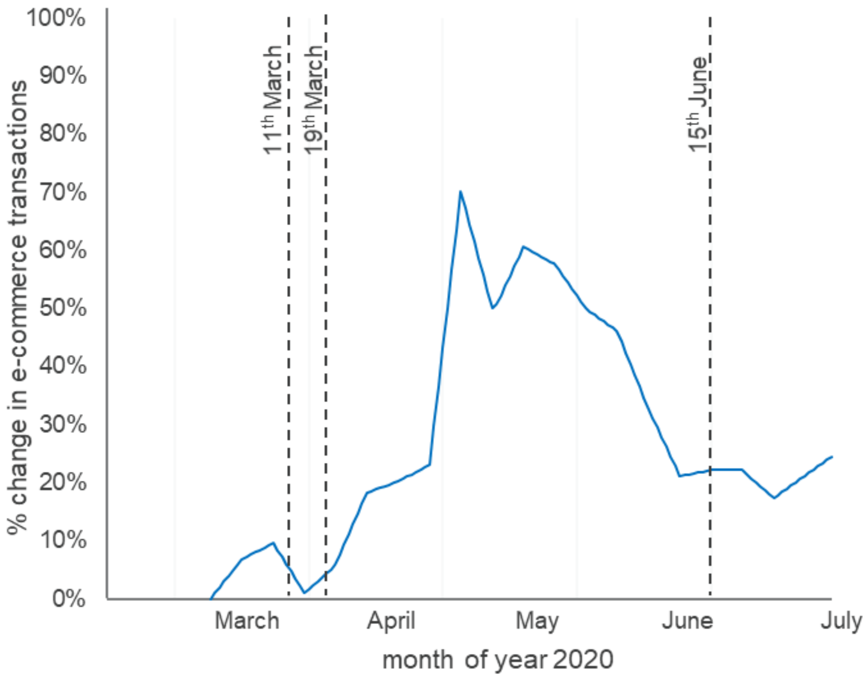



**Figure 1. E-commerce demand surge instigated by the COVID-19 pandemic**

On March 11, 2020, the World Health Organization (WHO) declared the novel coronavirus (SARSCoV2) outbreak causing the coronavirus disease (COVID-19) as a global pandemic (*7*). A level of panic ensued among buyers; the local brick-and-mortar stores witnessed opportunistic purchase behaviors resulting in long queues and hoarding of daily essentials (*8; 9*). Concomitantly, governments around the world enforced aggressive virus containment measures to build capacity to test, trace, and treat the infected. Following suit, the California State Government issued a stay-at-home order on March 19, 2020, which was lifted eventually on June 15, 2020 (*10; 11*). These measures led to widespread dysfunction in the retail sector. Retailers that largely relied on physical stores faced the brunt of the crisis, while other retailers who had some online presence managed through the crunch, though usually at the expense of significant cost cutting from reduced workforce and operations (*12*). The e-retailers on the other hand, particularly those selling essential goods, daily consumables, groceries, medications, and health-care products witnessed an unprecedented surge in demand (*13*). This shift in consumer shopping behaviors was consistently evident during periods of aggressive containment across different parts of the world [Czech Republic: Eger et al. (*14)*, France: Guthrie, Fosso-Wamba and Arnaud (*15)*, Germany: Koch, Frommeyer and Schewe (*16)*, India: Awasthi and Mehta (*17)*, New Zealand: Hall et al. (*18)*, Nigeria: Adunchezor and Akinade (*19)*, Slovakia: Valaskova, Durana and Adamko (*20)*]. Figure 1 showcases this shift in consumer shopping behavior in the form of increase in e-commerce transactions in the US in the first half of 2020.

Typically, e-retailers observe steady year-on-year growth in demand with a few high-probability low-severity fluctuations through the year, such as around the holiday season. To contend with such market dynamics, e-retailers regularly monitor and manage their distribution operations, which can include the redesign of vehicle delivery routes (short-term operational management), procurement or disposal of resources, e.g., staff and equipment (medium-term tactical management), or even reconfiguration of the distribution structure (long-term strategic management). However, the surge in e-commerce demand that ensued with the COVID-19 outbreak gave e-retailers little time to reassess and reconfigure decision-making concerning tactical but especially strategic operational management. Thus, constrained to a pre-pandemic level of resources, the e-retailers coped with the surge in demand while operating at a much lower level of service than usual by outsourcing last-mile operations in a range of ways: either to crowdsourced fleets for delivery, or to customers for pickup at collection-points, or to logistics service providers (LSP) for distribution (*21; 22*); as well as by prioritizing the delivery of essential goods at the cost of delayed service for other goods (*23*). Beyond providing delivery service to the typical customer, some e-retailers also received demand from frontline healthcare services for delivery of personal protective equipment such as gowns, masks, and gloves (*23*).

In considering the role of e-commerce distributions in ensuring the supply of essential goods during the COVID-19 pandemic, it is pertinent to assess the resilience of last-mile distribution operations in terms of e-retailers' ability to maintain and efficiently restore some level of service in the event of such low-probability, high-severity disruptions. Thus, for the purpose of the analyses, we (i) model e-retailer's last-mile distribution operations using continuous approximation (CA) techniques; (ii) develop the e-retailer's operational, tactical, and strategic decision-making to model its behavior pre-, peri-, and post- disruption; and (iii) evaluate e-retailer's performance under disruption, using the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) Resilience Triangle Framework, a novel performance-based qualitative-cum-quantitative domain-agnostic resilience assessment framework.

The next section summarizes the literature pertaining to resilience with a review of the various definitions and frameworks developed to assess resilience. The following sections present the CA framework modeling e-retailer's last-mile distribution operations, develop the logic to model the e-retailers' decision-making, and then introduce the R4 Resilience Triangle Framework, followed by a description of the case study. We then present the results establishing the dynamics of last-mile distribution for not only the market disruption that ensued with the COVID-19 pandemic but for other market disruptions in general, with varying characteristics. Finally, we discuss the key findings.

# Literature Review

In recent years, the research and development of sustainable systems that are economically viable, environmentally friendly, and equitable has garnered a lot of academic interest. Nonetheless, designing resilient systems that can resist, respond to, and recover from the consequences of disruptions is equally important for long-term system performance. In fact, a system that is not resilient to disruptions cannot be sustainable (*24*). Resilience, defined generally by Bruneau et al., is "… the ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disaster when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future disasters" (*3*). In the context of transportation systems, the literature (*25-28*) has generally characterized a resilient transportation system as one that can maintain and efficiently restore network functionality (passenger mobility and/or freight flows) in the event of a disruption (*29; 30*). The resilience literature offers a wide-range of such domain-specific (i.e., discipline-specific) interpretations. Yet, across domains, the literature has emphasized the need for organizational, social, economic, and engineering units of the system to consistently perform pre-disruption mitigation, appropriately respond during the disruption, and efficiently carry out post-disruption analysis and recovery, to build systemic resilience (*31*). Moreover, the various definitions and interpretations of resilience serve as foundations to develop robust frameworks to analyze and evaluate a system's response to disruptions.

To this end, the literature has developed many qualitative and quantitative frameworks (*31; 32*). The qualitative frameworks typically guide long-term decision-making for the strategic management of systems. For instance, the Resilience Capacity framework, one such qualitative framework, highlights the need for developing and maintaining absorptive, adaptive, and restorative capacities to establish a resilient system (*33*). Similarly, the R4 resilience framework underscores four salient properties for resilient operations, namely, robustness, the ability of the system to withstand disruption; redundancy, the extent to which the elements of the system are substitutable; resourcefulness, the ability to diagnose and prioritize problems as well as initiate solutions; and rapidity, the ability to restore functionality in a timely manner (*3*). The quantitative frameworks, on the other hand, offer precise assessments of a system's response to disruptions and in turn allow for operational, tactical, and strategic management of the system. To do so, these quantitative frameworks employ attribute-based methods that measure the properties of the system that bolster its resilience, or performance-based methods that gauge the system's performance under disruption (*34*). Resilience triangles (Figure 2)—introduced by Tierney and Bruneau (*2)* to depict and characterize the loss and subsequent recovery of a system's performance in the event of a disruption—are one of the most widely employed performance-based quantitative frameworks (*3; 35-38*). While these attribute- and performance-based methods typically use domain-agnostic indicators, the resilience literature has also developed domain-specific indicators, as is the case with topological metrics in the context of network analysis (*29; 34*).

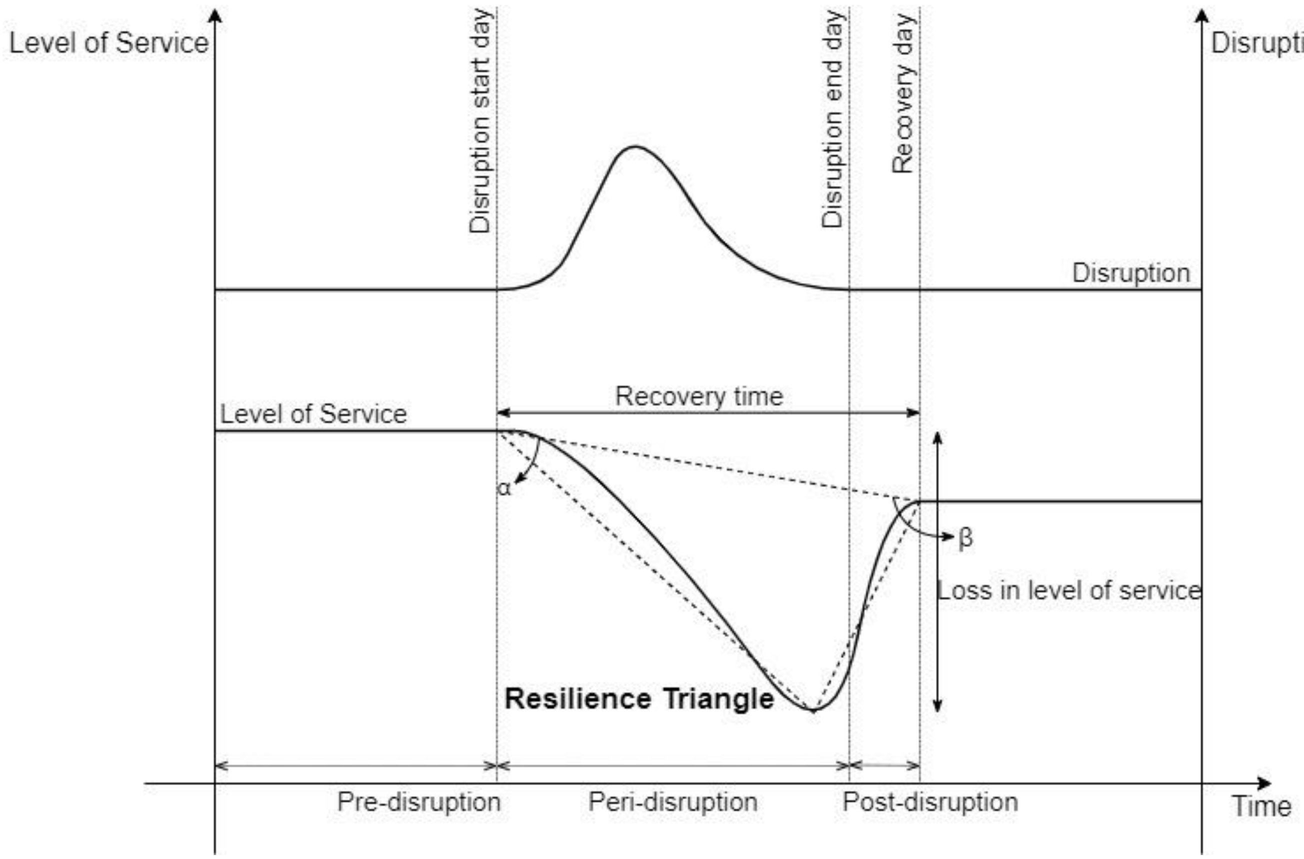



**Figure 2. Use of resilience triangle to assess system's performance under disruption**

The last-mile literature has extensively analyzed the sustainability of distribution operations under stochastic delivery environments with high-probability, low-severity fluctuations in the delivery environment (*39; 40*). Research on low-probability, high-severity disruptions in the context of transportation, however, is limited to disaster management, humanitarian logistics, and relief operations for earthquakes, tsunamis, hurricanes, terrorist attacks, etc. (*35; 41-46*). However, the total breakdown of global supply-chains and the consequent surge in e-commerce demand that occurred for months after the initial COVID-19 outbreak was unlike any other low-probability high-severity disruption and therefore warrants dedicated research. Since the outbreak, there has been a fresh interest in the resilience literature across varying domains. In the context of freight distribution, Hobbs (*47)* provided an early assessment of the impact of the pandemic on food supply-chains and projected a wider adaptation of online grocery and meal delivery services during the course of the pandemic. A year later, Hobbs (*48)* provided another assessment and argued for a sustained shift in demand for such online services even after the pandemic. And while the pandemic has indeed created new opportunities for e-commerce, Ali et al. (*49)* and Herold et al. (*50)* emphasized the need for mitigation strategies to protect the core functionality of the distribution structure with appropriate pre-disruption measures (i.e., ex-ante) and ad hoc post-disruption responses (i.e., ex-post) to protect the core functionality of the distribution structure (*9*). In particular, Burgos and Ivanov (*51)* underscored the importance of resolving transport/logistics bottlenecks to improve the level of service, and thus suggested that retailers secure additional stock or backup supplies to tackle demand surges. To this end, Moosavi and Hosseini (*52)* evaluated the increase in costs and improvement in resilience from such ex-ante measures, and thereby recommended retailers with critical supply-chains to secure additional stock for significant improvement in network resilience albeit at a high cost, while retailers with non-essential product distribution also secure a backup supply. Taking lessons from the pandemic, Singh et al. (*53)* and Srinivas and Marathe (*54)* proposed the use of drones/robots from a delivery truck functioning as a mobile warehouse carrying high-demand products in anticipation of customer requests (anticipatory shipping) to limit product shortages and reduce customer lead-time in future disruptions. Guthrie, Fosso-Wamba and Arnaud (*15)* showcased the use of the react-cope-adapt framework to predict the evolution of consumer shopping behaviors during the course of the pandemic, thus enabling retailers to fine-tune and manage inventory for anticipatory shipping. These studies highlight the newfound interest in understanding the impact of disruptions to better prepare for and respond to them in the future.

Thus, considering the role of e-commerce last-mile distribution in ensuring the delivery of essential goods to the typical customer and frontline healthcare services during the COVID-19 pandemic, the objective of this work is to assess resilience of last-mile distribution operations in terms of e-retailers' ability to maintain and efficiently restore service levels in the event of such low-probability high-severity disruptions. To cope with the disruption, this study assumes that the e-retailer will make use of one of the many outsourcing channels at its disposal, while delaying delivery for demand beyond the expanded distribution capacity. The outsourcing channels include delivery via a crowdsourced fleet, customer pickup via collection-points, or distribution via an LSP operating from its micro-hubs using cargo-bikes (or other small and light vehicles). To this end, we propose R4 Resilience Triangle Framework, integrating the R4 resilience framework (*3*) and resilience triangle concept (*2*). Unlike the resilience triangle or R4 framework alone, the integrated framework offers a sophisticated quantification of the qualitative properties of resilience, i.e., robustness, redundancy, resourcefulness, and rapidity. With this, the study aims to develop a holistic understanding concerning the capability of e-retailers' last-mile distribution operations to maintain and efficiently restore service levels under disruption.

# Methods

This study develops analyses for an e-retailer making deliveries in a service region of size $A$, using a homogenous fleet of delivery trucks operating from an e-commerce fulfillment facility located at $(\rho_x, \rho_y)$ relative to the center of this service region. We assume that the e-retailer organizes its distribution structure in line with the lean management principles typical of e-commerce supply-chains, thus allowing for low-cost just-in-time deliveries. While such a distribution structure can cope with minor disruptions, a severe unforeseen disruption can put the e-retailer at risk of operating at a much lower level of service than usual. Thus, to assess the last-mile distribution resilience against a low-probability high-severity disruption, we develop the response of this e-retailer to the kind of market disruption witnessed in the early months of the COVID-19 pandemic. In particular, we model a market disruption resulting from inhibited public movement, leading to reduced traffic congestion ($\phi_t$) and increased e-commerce demand ($N_t$). To cope with this market disruption, the e-retailer may outsource some operations either via a crowdsourced fleet for delivery, or via $N^{cp}$ collection-points for customer pickup, or via an LSP for distribution from $N^{mh}$ micro-hubs using cargo-bikes. Below is a list of notations specific to the e-retailer's distribution channel, but when used with a prime superscript these notations refer to the outsourcing channel.

*Indices*

| | |
|---|---|
| $t$ | : Subscript for time (in days) |
| $e$ | : Subscript for emissions |

*Distribution structure parameters*

| | |
|---|---|
| $A$ | : Size of the service region |
| $\rho_x, \rho_y$ | : E-commerce fulfillment facility location relative to the center of the service region |
| $\phi_t$ | : Congestion factor (speed relative to free-flow speed) on day $t$ |
| $N_t$ | : Customer demand on day $t$ |
| $N^{cp}$ | : Number of collection-points |
| $N^{mh}$ | : Number of micro-hubs |
| $\delta_t$ | : Customer density on day $t$ |
| $\delta^{cp}$ | : Collection-point density |
| $\delta^{mh}$ | : Micro-hub density |
| $V$ | : Collection-point capacity |
| $\bar{N}_t$ | : Distribution structure capacity on day $t$ |

*Distribution operations parameters*

| | |
|---|---|
| $f$ | : Fleet size |
| $m$ | : Number of delivery tours per vehicle |
| $L_t$ | : Delivery tour length on day $t$ |
| $T_t$ | : Delivery tour time on day $t$ |
| $\rho$ | : Long-haul length |
| $\Lambda_t$ | : Long-haul travel time on day $t$ |
| $k$ | : Continuous approximation (CA) constant |
| $C_t^c$ | : Number of customer visits per delivery tour on day $t$ |
| $C_t^{cp}$ | : Number of collection-point visits in a delivery tour on day $t$ |
| $C_t^{mh}$ | : Number of micro-hub visits in a delivery tour on day $t$ |
| $\theta$ | : Number of customers served per delivery stop |
| $p_t$ | : Share of customers served via outsourcing channel |
| $p_u$ | : Maximum permissible outsourcing share |

*Vehicle parameters*

| | |
|---|---|
| $VC$ | : Vehicle capacity |
| $v_{out}$ | : Vehicle free-flow speed outside the service region |
| $v_{in}$ | : Vehicle free-flow speed inside the service region |
| $\tau_{sF}$ | : Service time loading/unloading packages at a facility (per customer) |
| $\tau_{sC}$ | : Service time delivering packages to a customer |
| $r_f$ | : Rate of fuel consumption |
| $r_e$ | : Rate of emissions |

*Cost parameters*

| | |
|---|---|
| $\Pi_t$ | : Distribution cost on day $t$ |
| $F_{fc}$ | : Facility fixed cost |
| $PC$ | : Vehicle purchase cost |
| $\pi_d$ | : Driver cost |
| $\pi_m$ | : Maintenance cost |
| $\pi_f$ | : Fuel cost |
| $\pi_e$ | : Emission cost |

*Other parameters*

$t_o$ : Day 1
$t_s$ : Disruption start day
$t_r$ : Recovery day
$t_e$ : Disruption end day
$W$ : Working hours in a day
$\eta$ : Amortization factor
$\psi^{cs}$ : Binary variable ($\psi^{cs} = 1$ if outsourcing via crowdsourced fleet)
$\psi^{cp}$ : Binary variable ($\psi^{cp} = 1$ if outsourcing via customer-led collection-point pickup)
$\psi^{mh}$ : Binary variable ($\psi^{mh} = 1$ if outsourcing via micro-hubs operated by logistics service provider)
$\bar{f}$ : Fleet size limit

## Modeling last-mile distribution operations using continuous approximation (CA)

To model the distribution and outsourcing operations, this work employs the CA-based last-mile delivery model developed by Jaller and Pahwa (*1*). *Equations (1)-(16)* present last-mile delivery model in the context of this work. We encourage interested readers to refer to the cited work for a detailed review of the continuous approximation-based last-mile delivery model.

### Pre-disruption $(t \in [t_o, t_s))$ distribution operations:

We assume that prior to the surge in demand ($t \in [t_o, t_s)$), the e-retailer operates independently, with its fleet of delivery trucks making all the delivery tours. Each delivery tour consists of: the long-haul, i.e., the journey from the e-commerce fulfillment facility to the first customer-stop and likewise from the last customer-stop back to the facility; and the last-mile, the journey between the first and last customer-stops. Hence, the length of this delivery tour (*Equation (1)*) is the sum of back-and-forth long-haul distance ($\rho$) and the last-mile distance, represented by each term in the equation, respectively. And the delivery tour time (*Equation (2)*) is the sum of the service time loading packages at the facility ($\tau_{sF}$ per package), the long-haul travel time ($\Lambda_t$), the last-mile travel time, and the service time delivering packages at customer-stops ($\tau_{sC}$ per customer), represented by each term in the equation, respectively. Note, the long-haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility (refer to *Equations (15) and (16)*), while the last-mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+$, and inversely proportional to the square root of stop density ($\delta_t/\theta$). Note, $\theta$ represents the number of customers consolidated per stop.

$$L_t = 2\rho + \frac{k[C_t^c/\theta]^+}{\sqrt{\delta_t/\theta}} \quad (1)$$

$$T_t = C_t^c \tau_{sF} + 2\Lambda_t + \frac{k[C_t^c/\theta]^+}{v_{in}\phi_t\sqrt{\delta_t/\theta}} + C_t^c \tau_{sC} \quad (2)$$

### Peri-disruption ($t \in [t_s, t_e]$)/Post-disruption ($t \in (t_e, t_r]$) distribution operations:

To cope with a low-probability high-severity surge in demand ($t \in [t_s, t_r]$), this work assumes that the e-retailer will choose to outsource $p_t$ share of its deliveries, either via a crowdsourced fleet for delivery, collection-points for customer pickup, or via an LSP for distribution from its micro-hubs using cargo-bikes (Figure 3). *Equations (3)-(16)* model the distribution operations for the e-retailer and outsourcing channel combined distribution structure.

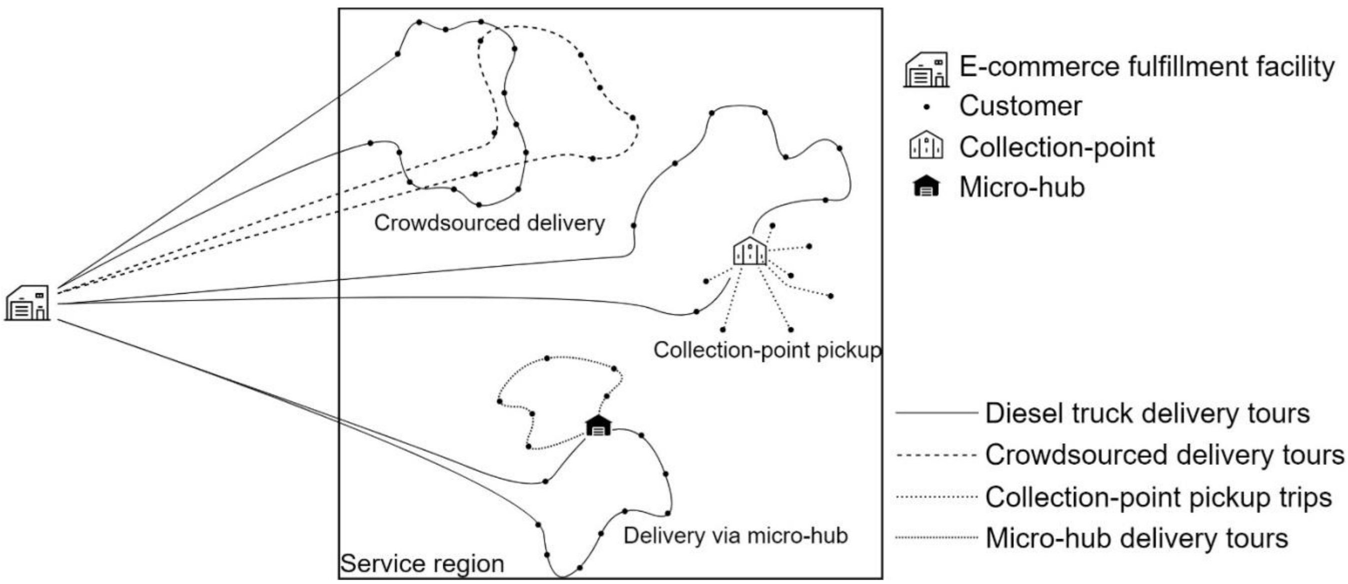



**Figure 3. Distribution operations of e-retailer plus outsourcing channel combined**

## Crowdsourced delivery

The crowdsourced operations in this study take their inspiration from the Amazon Flex program (*55*). Much like the e-retailer's delivery trucks, the crowdsourced drivers collect packages at the e-commerce fulfillment facility before embarking on e-retailer designed tours. The length of this delivery tour (*Equations (3) and (5)*) is the sum of long-haul and last-mile distances, represented by each term in the equations, respectively. And the delivery tour time (*Equations (4) and (6)*) is the sum of the service time loading packages at the facility, the long-haul travel time, the last-mile travel time, and the service time delivering packages to the customers, represented by each term in the equations, respectively. Note, *Equations (3)* and *(4)* model the delivery tour of the e-retailer's truck, while *Equations (5)* and *(6)* model the delivery tour of the crowdsourced vehicle.

$$L_t = 2\rho + \frac{k[C_t^c/\theta]^+}{\sqrt{\delta_t(1-p_t)/\theta}} \quad (3)$$

$$T_t = C_t^C\tau_{sF} + 2\Lambda_t + \frac{k[C_t^c/\theta]^+}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta}} + C_t^c\tau_{sC} \quad (4)$$

$$L_t' = 2\rho + \frac{k\left[C_t^{c\prime}/\theta\right]^+}{\sqrt{\delta_t p_t/\theta}} \quad (5)$$

$$T_t' = C_t^{C\prime}\tau_{sF}' + 2\Lambda_t' + \frac{k\left[C_t^{c\prime}/\theta\right]^+}{v_{in}'\phi_t\sqrt{\delta_t p_t/\theta}} + C_t^{c\prime}\tau_{sC}' \quad (6)$$

## Customer pickup at collection-points

Unlike crowdsourcing, where the outsourcing channel operates independently, here the e-retailer must fulfill the collection-points using its fleet of delivery trucks before customers can travel to one of the collection-points to collect their packages. Note, the model assumes that the e-retailer has located $N^{cp}$ collection-points randomly and uniformly in the service region, each with a capacity to hold $V$ packages. Thus, the delivery tour consists of the long-haul and the last-mile, with the latter including visits to the customers and collection-points. Therefore, the delivery tour length (*Equation (7)*) is the sum of the long-haul and last-mile distances, represented by each term in the equation, respectively. And the delivery tour time (*Equation (8)*) is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at customer-stops, and the service time unloading packages at the collection-points, represented by each term in the equation, respectively. The customer's collection-point visit (trip) is estimated by the average distance from customer-stop to the nearest collection-point (*Equations (9)* and *(10)*).

$$L_t = 2\rho + \frac{k\left([C_t^c/\theta]^+ + [C_t^{cp}]^+\right)}{\sqrt{\delta_t(1-p_t)/\theta + \delta^{cp}}} \quad (7)$$

$$T_t = (C_t^C + V)\tau_{sF} + 2\Lambda_t + \frac{k\left([C_t^c/\theta]^+ + [C_t^{cp}]^+\right)}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta + \delta^{cp}}} + C_t^c\tau_{sC} + V\tau_{sF} \quad (8)$$

$$L_t' = 2\left(\frac{2}{3}\sqrt{A/N^{cp}}\right) \quad (9)$$

$$T_t' = \frac{2\rho'}{v_{in}'\phi_t} + \tau_{sC}' \quad (10)$$

## Distribution via micro-hubs operated by a logistics service provider (LSP)

We assume the LSP to operate from $N^{mh}$ identical micro-hubs located randomly and uniformly in the service region, each with a fleet of cargo-bikes or other small/light delivery vehicles. The e-retailer must fulfill the LSP's micro-hubs using its fleet of delivery trucks before the cargo-bikes from these micro-hubs can embark for last-mile deliveries. Thus, the delivery truck's delivery tour consists of the long-haul and the last-mile, with the latter including visits to the customers and micro-hubs. The delivery truck's delivery tour length (*Equation (11)*) is therefore the sum of the long-haul and the last-mile distances, represented by each term in the equation, respectively. And the delivery truck's delivery tour time (*Equation (12)*) is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at the customer-stops, and the service time unloading packages at the micro-hubs, represented by each term in the equation, respectively. On the other hand, a cargo-bike's delivery tour consists of: the long-haul, i.e., the journey from the micro-hub to the first customer-stop and likewise from the last customer-stop back to the micro-hub; and the last-mile, the journey between the first and last customer-stops. The cargo-bike's delivery tour length (*Equation (13)*) is therefore the sum of the long-haul and the last-mile distances, represented by each term in the equation, respectively. And the cargo-bike's delivery tour time (*Equation (14)*) is the sum of the service time loading packages at the micro-hub, the long-haul travel time, the last-mile travel time, and the service time delivering packages at the customer-stops, represented by each term in the equation, respectively.

$$L_t = 2\rho + \frac{k\left([C_t^c/\theta]^+ + [C_t^{mh}]^+\right)}{\sqrt{\delta_t(1-p_t)/\theta + \delta^{mh}}} \tag{11}$$

$$T_t = \left(C_t^C + C_t^{mh}\frac{Np_t}{N^{mh}}\right)\tau_{sF} + 2\Lambda_t + \frac{k\left([C_t^c/\theta]^+ + [C_t^{mh}]^+\right)}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta + \delta^{mh}}} + C_t^c\tau_{sC} + C_t^{mh}\frac{Np}{N^{mh}}\tau_{sF} \tag{12}$$

$$L_t' = 2\left(\frac{2}{3}\sqrt{A/N^{mh}}\right) + \frac{k\left[C_t^{c'}/\theta\right]^+}{\sqrt{\delta_t p_t/\theta}} \tag{13}$$

$$T_t' = C_t^{C'}\tau_{sF}' + \frac{2\rho'}{v_{in}'\phi_t} + \frac{k\left[C_t^{c'}/\theta\right]^+}{v_{in}'\phi_t\sqrt{\delta_t p_t/\theta}} + C_t^{c'}\tau_{sC}' \tag{14}$$

Where,

$$\rho = \begin{cases} |\rho_x| + |\rho_y| \text{ if } |\rho_x| \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ |\rho_x| + \rho_y^2/\sqrt{A} + \sqrt{A}/4 \text{ if } |\rho_x| \geq \sqrt{A}/2 \text{ and } |\rho_y| < \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \sqrt{A}/4 + |\rho_y| \text{ if } |\rho_x| < \sqrt{A}/2 \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \rho_y^2/\sqrt{A} + \sqrt{A}/2 \text{ if } |\rho_x| \text{ and } |\rho_y| < \sqrt{A}/2 \end{cases} \tag{15}$$

$$\Lambda_t = \frac{1}{\phi_t}\begin{cases} \frac{\rho}{v_{out}} + \sqrt{A}\left(\frac{1}{v_{in}} - \frac{1}{v_{out}}\right) \text{ if } |\rho_x| \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ \frac{|\rho_x|}{v_{out}} + \frac{(\rho_y^2/\sqrt{A} + \sqrt{A}/4)}{v_{in}} + \frac{\sqrt{A}}{2}\left(\frac{1}{v_{in}} - \frac{1}{v_{out}}\right) \text{ if } |\rho_x| \geq \sqrt{A}/2 \text{ and } |\rho_y| < \sqrt{A}/2 \\ \frac{(\rho_x^2/\sqrt{A} + \sqrt{A}/4)}{v_{in}} + \frac{|\rho_y|}{v_{out}} + \frac{\sqrt{A}}{2}\left(\frac{1}{v_{in}} - \frac{1}{v_{out}}\right) \text{ if } |\rho_x| < \sqrt{A}/2 \text{ and } |\rho_y| \geq \sqrt{A}/2 \\ \frac{\rho}{v_{in}} \text{ if } |\rho_x| \text{ and } |\rho_y| < \sqrt{A}/2 \end{cases} \tag{16}$$

The reader is referred to Jaller and Pahwa (*1*) for a detailed review of the model (*Equations (1)-(16)*.

## Developing e-retailer's decision-making in the pre-, peri-, and post-disruption phase

In the pre-disruption phase ($t \in [t_o, t_s)$), the model assumes that the e-retailer observes a stable daily demand of $N_o$ customers. To cater to this demand, the e-retailer organizes its distribution structure in line with lean-management practices, thereby minimizing the total distribution cost - $\Pi_t$ (*Equation (17)*) by considering the location of the e-commerce fulfillment facility ($\rho_x, \rho_y$), the fleet size ($f_t$), the number of delivery tours per vehicle ($m_t$), and the number of customers served per delivery tour ($C_t^c$), subject to vehicle capacity (*Equation (18)*), working hours (*Equation (19)*), and service constraints (*Equation (20)*). This total cost includes amortized fixed costs—i.e., facility fixed costs and fleet purchase costs; operational costs—i.e., driver, maintenance, and fuel costs; and emission costs. To this end, let ($\rho_{x_o}, \rho_{y_o}$) denote the optimal e-commerce fulfillment facility location and let $f_o$ be the optimal e-retailer's delivery truck fleet size resulting from minimizing the pre-disruption distribution cost.

$$\min_{\{\rho_x, \rho_y, f_t, m_t, C_t^c\}} \Pi_t = (F_{fc} + PC f_t)/\eta + T_t m_t f_t \pi_d + L_t m_t f_t (\pi_m + r_f \pi_f + \Sigma_e r_e \pi_e) \tag{17}$$

Subject to,

$$C_t^c \leq VC \tag{18}$$

$$T_t m_t \leq W \tag{19}$$

$$C_t^c m_t f_t = N_o \tag{20}$$

$$\forall\, t \in [t_o, t_s)$$

In the peri- and post-disruption phase ($t \in [t_s, t_r]$), to serve the daily demand of $N_t$ customers ($N_t > N_o$) plus the previous unmet demand of $N_{t-1}^u$ customers, the model assumes that the e-retailer will outsource some of its operations via the outsourcing channels at its disposal. In particular, if the combined e-retailer and outsourcing channel distribution structure capacity of $\overline{N}_t$ customers (*Equation (21)*) is sufficient to cater to the increased e-commerce demand of $N_t + N_{t-1}^u$ customers, then the e-retailer minimizes the distribution cost, $\Pi_t$ (*Equation (22)*), by outsourcing deliveries for $(N_t + N_{t-1}^u)p_t$ customers while serving the remaining customers using its available fleet of delivery trucks, optimizing for the share of operations to outsource ($p_t$), operational parameters of the outsourcing channel ($f_t', m_t', C_t^{c\prime}$), and operational parameters of its delivery tours ($m_t, C_t^c$), subject to vehicle capacity (*Equations (24) and (25)*), working hours (*Equations (26) and (27)*), service (*Equations (28) and (29)*), and resource constraints (*Equations (30) and (31)*). However, if the combined distribution capacity of $\overline{N}_t$ customers falls short of the increased e-commerce demand, then the combined distribution structure caters to the $\overline{N}_t$ customers, while delaying delivery for $N_t^u = N_t + N_{t-1}^u - \overline{N}_t$ customers to the next day. Note, the distribution cost here includes fixed, operational, and emissions costs for the combined distribution structure.

$$\max_{\{m_t, C_t^c, f_t', m_t', C_t^{c'}, p_t\}} \bar{N}_t = C_t^C m_t f_o + C_t^{C'} m_t' f_t' \tag{21}$$

$$\begin{aligned}\min_{\{m_t, C_t^c, f_t', m_t', C_t^{c'}, p_t\}} \Pi_t = {} & (F_{fc} + PCf_o)/\eta + (F_{fc}' + PCf_t')/\eta + \\ & T_t m_t f_o \pi_d + T_t' m_t' f_t' \pi_d' + \\ & L_t m_t f_o(\pi_m + r_f \pi_f + \Sigma_e r_e \pi_e) + \\ & L_t' m_t' f_t'(\pi_m' + r_f' \pi_f' + \Sigma_e r_e' \pi_e)\end{aligned} \tag{22}$$

Subject to,

$$N = \begin{cases} \bar{N}_t \text{ if the objective is to maximize distribution capacity} \\ N_t + N_{t-1}^u \text{ if the objective is to minimize distribution cost} \end{cases} \tag{23}$$

$$(C_t^c + \psi^{cp} V + \psi^{mh} C_t^{mh} Np_t / N^{mh}) \leq VC \tag{24}$$

$$C_t^{c'} \leq VC' \tag{25}$$

$$T_t m_t \leq W \tag{26}$$

$$T_t' m_t' \leq W \tag{27}$$

$$C_t^c m_t f_o = N(1 - p_t) \tag{28}$$

$$C_t^{c'} m_t' f_t' = Np_t \tag{29}$$

$$f_t' \leq \bar{f}' \tag{30}$$

$$p_t \leq p_u \tag{31}$$

$$\forall\, t \in [t_s, t_r]$$

*Equation (32)* shows facility fixed cost (per sq. ft.) in the service region as a function of facility location, developed using CoStar (*56*) sales and lease data for industrial facilities in southern California. Note, to estimate the size of the distribution facility, this work assumes a consolidation of 0.2 customers per sq. ft based on interviews and field study experience.

$$F_{fc} = \$356.37(\rho_x^2 + \rho_y^2)^{-0.116}/sq.ft. \tag{32}$$

## Evaluating e-retailer's performance under disruption

We further developed the framework to assess the e-retailer's performance under disruption in the form of level of service. Here, the level of service is a performance indictor evaluated as the ratio of demand served to total demand, thus it is bounded between zero and one. A zero indicates a total loss of functionality, a one, fully functional last-mile service, and a value between, a partial level of functionality with unmet demand. We characterize a drop in level of service as a consequence of the disruption using the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) Resilience Triangle Framework (Figure 4). This framework quantifies robustness, i.e., the ability of the system to withstand disruption, as the gap between the nadir and zero level of service line (*Equation (33)*). Redundancy, the extent to which the elements of the system are substitutable, is the average downward slope towards the nadir (*Equation (34)*). Resourcefulness, the ability to diagnose and prioritize problems as well as initiate solutions, is quantified as the ratio of recovered level of service to the drop in level of service at the nadir (*Equation (35)*). And rapidity, the capability to restore functionality in a timely manner, is the average upward slope towards recovery from the nadir (*Equation (36)*).

$$Robustness = 1 - OB \tag{33}$$
$$Redundancy = \beta_1/(\pi/2) \tag{34}$$
$$Resourcefulness = OD/OB \tag{35}$$
$$Rapidity = \beta_2/(\pi/2) \tag{36}$$

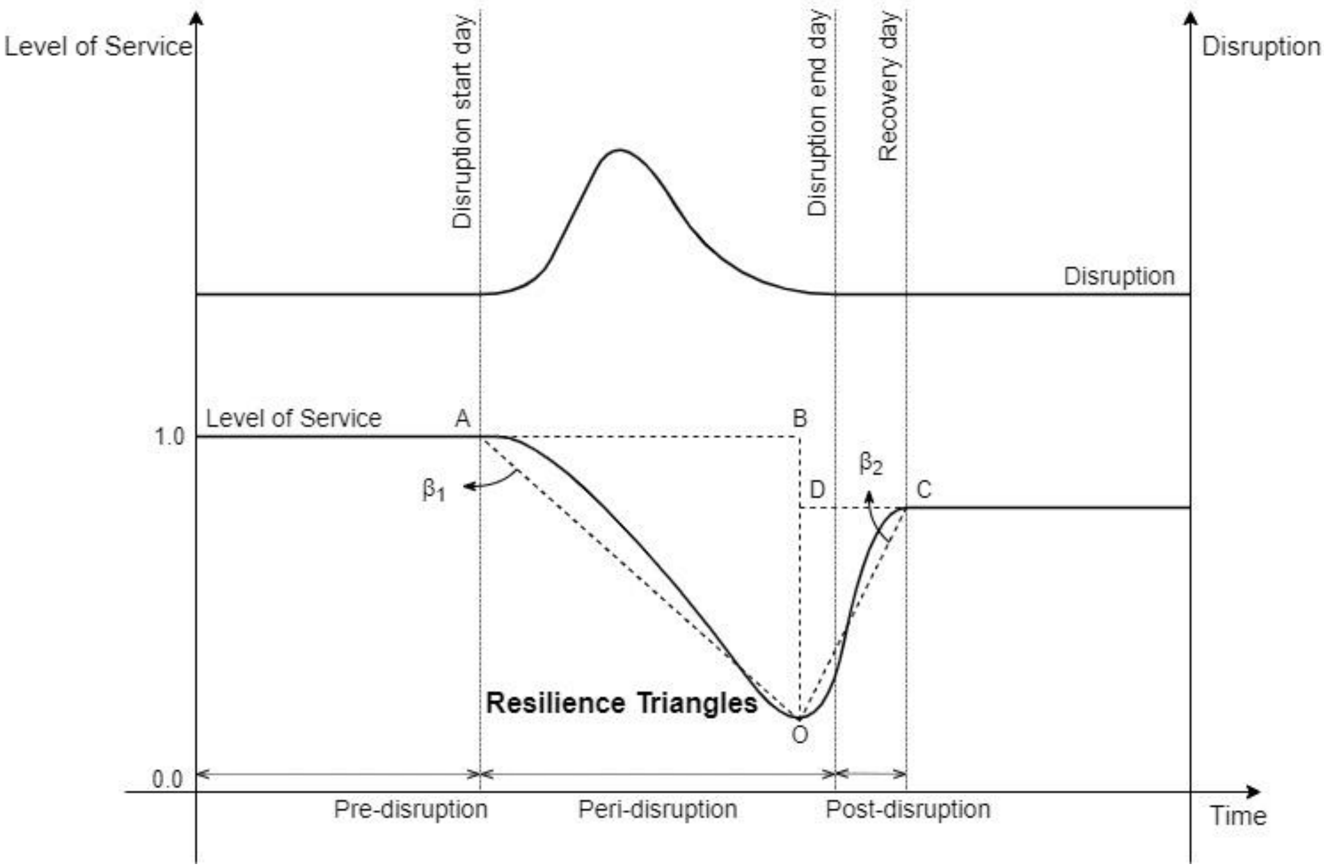



**Figure 4. Characterizing system's level of service under disruption using resilience triangles**

This performance-based qualitative-cum-quantitative framework allows one to assess the resilience of last-mile distribution operations under any disruption. Moreover, this framework is not specific to last-mile logistics or transportation systems, but is domain-agnostic, and thus can be employed across domains to assess resilience of any system under disruption.

In addition to determining the resilience metrics, we evaluate the e-retailer's performance with operational metrics that quantify the extent of delayed deliveries, as well as economic metrics that evaluate the direct, indirect, and total loss to the e-retailer as a result of the disruption. These metrics are further detailed in the Empirical Results section.

# Case Study

This study analyzes a fairly large-sized e-retailer with a market share of ~20%, serving the city of Los Angeles, a 475 sq. mi. service region with ~150,000 pre-disruption daily online customers located randomly and uniformly in the region (*1; 5*). Using daily internet transactions data (Figure 5), we model the pandemic-instigated surge in demand as a double logistic model (*Equation* (38)) commonly deployed to model COVID-19 spread and associated second-order effects (*57-59*), rendering a peri-disruption peak demand for the e-retailer of 47.8k customers and a post-disruption demand of 36k customers (Figure 5Figure 5). Thus, in the pre-disruption stage, the e-retailer organizes its distribution structure to deliver 30k packages daily with low-cost just-in-time service consistent with lean-management principles of supply-chain. In the peri-/post- disruption stage, constrained to the pre-disruption optimal distribution structure, the e-retailer outsources part of its operations to cope with the surge in demand with: delivery via a crowdsourced fleet of 565 light-duty trucks; customer pickup at 200 randomly and uniformly located collection-points, each with a capacity of 50 packages (assuming at most 85% customers are willing to self-collect); or distribution via an LSP operating 10 randomly and uniformly located micro-hubs, each with 22 cargo-bikes.

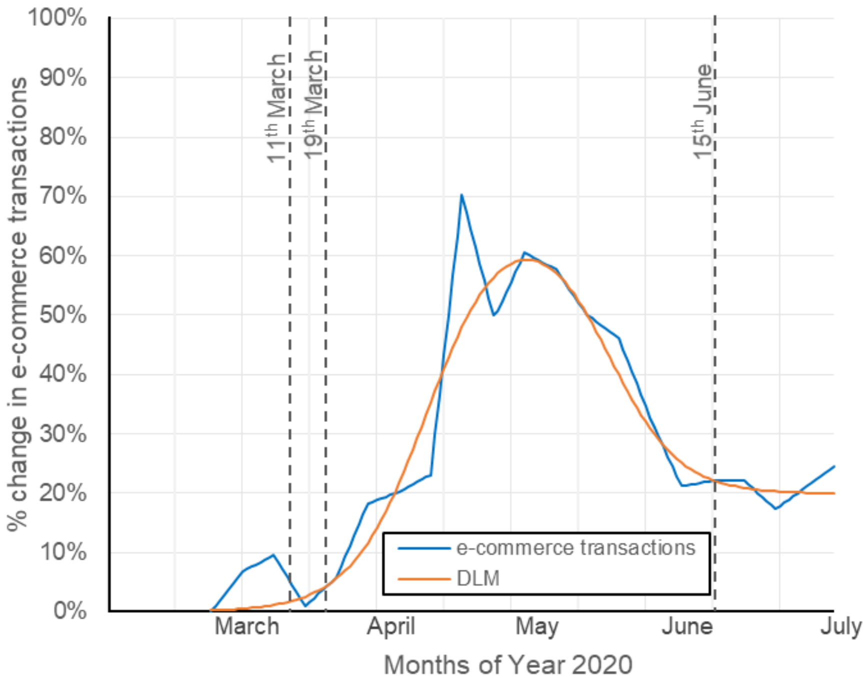
$$y_t = (Q_t/Q_o - 1) * 100 \tag{37}$$

$$y_t = \frac{\alpha_1}{1 + \exp(-(t - \mu_1)/\theta_1)} - \frac{\alpha_2}{1 + \exp(-(t - \mu_2)/\theta_2)} \tag{38}$$

Where,

$Q_t$: e-commerce transactions
$y_t$ : percentage change in e-commerce transactions
$\alpha_1$: growth factor (% increase to peak disruption)
$\alpha_2$: decay factor (% decrease from peak disruption)
$\mu_1$: growth half-life (days to half the increase to peak disruption)
$\mu_2$: decay half-life (days to half the decrease from peak disruption)
$\theta_1$: Inverse growth rate (inverse of the rate of increase to peak disruption)
$\theta_2$: Inverse decay rate (inverse of the rate of decrease from peak disruption)

The crowdsourcing strategy detailed here takes its inspiration from the Amazon Flex Program, wherein Amazon hires drivers on an on-demand basis and gives them a dispatch plan to make deliveries using their personal vehicles. We assume 565 crowdsourced drivers with their light-duty trucks to be available at the disposal of the e-retailer for crowdsourced deliveries. The e-retailer remunerates the crowdsourced drivers on an hourly basis only, and not for their fuel costs or vehicle maintenance expenses, consistent with the Amazon Flex Program. Due to such limited incentives, the analysis here assumes the crowdsourced drivers to be willing to only do one delivery tour for the e-retailer.




DLM: Double Logistic Model

$y_t = 0.685/(1 + \exp(-(t - 49.373)/8.447)) - 0.486/(1 + \exp(-(t - 89.512)/7.885)); R^2 = 0.937$

**Figure 5. Modeling e-commerce demand surge instigated by the COVID-19 pandemic**

The collection-points in this study are in fact lockers with a capacity of 50 packages. To make use of the collection-points, the e-retailer must ship packages from its e-commerce fulfillment facility to the 200 randomly and uniformly located collection-points using its fleet of delivery trucks, from which the customers collect the packages. Prior to the pandemic, e-commerce witnessed as many as 37% of customers willing to collect package at an alternate location, i.e. other than the customer's home or office (*60*). While this willingness to collect packages at an alternate location could vary during the course of the pandemic, for the purpose of this study, we assume that at most 85% of the e-retailer's customers will be willing to collect packages from the nearest collection-point.

With the LSP, the e-retailer must ship packages from its e-commerce fulfilment facility to the 10 randomly and uniformly located micro-hubs using its fleet of delivery trucks, from which the LSP delivers packages to the customer's doorstep using a fleet of 220 electric cargo-bikes. This study assumes the LSP to equip its micro-hubs with 220 Level 2 chargers, priced at $3k each.

We design these outsourcing channels and plan the available resources such that the e-retailer can just about cope with the pandemic-instigated surge in demand, i.e., without any loss in level of service. For simplicity, we assume no direct loss in the e-retailer's distribution capacity with continued availability of resources (staff and drivers) during the course of the pandemic. Nonetheless, we then limit the resources available to the e-retailer from the outsourcing channel to elicit reduced distribution capacity to evaluate e-retailer's ability to maintain and restore level of service from the disruption. Moreover, the analyses assume that a relative increase in demand can also represent a reduction of internal distribution capacity. To this end, this study develops a sensitivity analysis to further evaluate the e-retailer's performance under disruptions in general.

Table 1 shows the relevant features for each of the vehicle-type deployed in the distribution process. For the analyses, this study assumes a consolidation of 3 deliveries per stop ($\theta = 3$). To evaluate emissions costs, this work accounts for $CO_2$, CO, $NO_x$, and PM emissions from last-mile distribution, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively (*61; 62*). In addition to the surge in demand, we also model reduced traffic congestion—observed as a consequence of inhibited public movement owing to the various virus containment measures, as a double logistic model similar to the surge in demand.

**Table 1. Vehicle characteristics**

| Vehicle characteristics | | Class-5 DT | LDT | PC | ECB |
|---|---|---|---|---|---|
| Purchase cost [a] ($) | $PC$ | 80k | - | - | 9.5k* |
| Capacity (customers per tour) | $VC$ | 360 | 30 | 1 | 30 |
| Speed outside the service region (mph) | $v_{out}$ | 55 | 60 | 60 | 10 |
| Speed inside the service region (mph) | $v_{in}$ | 20 | 25 | 25 | 10 |
| Service time at facility (mins per customer) | $\tau_{sF}$ | 0.3 | 0.5 | - | 0.3 |
| Service time at customer (mins) | $\tau_{sC}$ | 1.0 | 0.5 | 1.0 | 0.5 |
| Driver cost [b] ($/hour) | $\pi_d$ | 35 | 35 | - | 35 |
| Maintenance cost [b] ($/mi) | $\pi_m$ | 0.20 | - | - | 0.02 |
| Fuel cost [c] ($/gal, $/kWh) | $\pi_f$ | 3.86 | - | - | 0.12 |
| Fuel consumption rate [a] (mi/g, mi/kWh) | $r_f$ | 0.1 | 0.05 | 0.03 | 0.29 |
| Range (mi) | $R$ | - | - | - | 30 |
| $CO_2$ emission rate [d] (g/mi) | $r_{CO_2}$ | 1049.38 | 386.1 | 303 | 0 |
| CO emission rate [d] (g/mi) | $r_{CO}$ | 0.77 | 1.77 | 1.09 | 0 |
| $NO_x$ emission rate [d] (g/mi) | $r_{NO_x}$ | 4.1 | 0.17 | 0.08 | 0 |
| PM emission rate [d] (g/mi) | $r_{PM}$ | 0.132 | 0.0026 | 0.002 | 0 |

DT – Diesel Truck, ECB – Electric Cargo Bike, LDT – Light Duty Truck (crowd-sourcing vehicle), PC – Passenger Car

[a] Jaller, Pineda and Ambrose *(63)* [b] Caltrans *(64)* [c] AAA *(65)* [d] California Air Resource Board *(66)*

*Charging infrastructure cost included

# Empirical Results

The empirical results detail the e-retailer's response and assess the resilience of last-mile distribution operations against the market disruption instigated by the COVID-19 pandemic. In the first part of this analysis, we detail the distribution operations under the market disruption that ensued with the COVID-19 pandemic. Recall that we have designed these outsourcing channels and planned the available resources such that the e-retailer can just about cope with the pandemic-instigated surge in demand. Thus, in the second part we limit the distribution capacity of the outsourcing channels to evaluate e-retailer's performance and therefore to assess the resilience of its last-mile distribution operations under the pandemic-instigated market disruption. In addition to the primary analysis, we perform a sensitivity analysis to assess the e-retailer's performance under disruptions (in general) with varying characteristics to guide the e-retailer's decision-making against future disruptions.

## Primary analysis - COVID-19 instigated market disruption

As discussed in the Case Study, prior to the COVID-19 pandemic, the e-retailer serves a total of 30k customers daily, delivering just-in-time to minimize its distribution cost (*Equation (17)-(20)*). This minimization renders a pre-disruption distribution cost of $50.35k for the e-retailer operating from an e-commerce fulfillment facility optimally located at 6.45 miles from downtown LA, with an optimal fleet size of 98 class-5 diesel trucks loaded with a less-than-truckload number of packages at 85% load utilization to comply with driver working-hours. However, with the onset of the COVID-19 pandemic, the local authorities impose aggressive virus containment measures which significantly inhibit public movement and thus trigger a market disruption with a 2-week lag ($t_o = 1, t_s = 14$) including a surge in e-commerce demand (*Equation (39)*) and a reduction in traffic congestion (*Equation (40)*). In particular, the e-retailer observes a peak peri-disruption demand of 47.8k customers and a stable post-disruption demand of 36k customers daily, with traffic conditions improving to almost as good as free-flow conditions in the peri-disruption stage before returning back to pre-disruption levels after the disruption (Figure 6).

$$N_t = N_o\left(1 + \frac{0.685}{\left(1+\exp\left(\frac{-(t-49.373)}{8.447}\right)\right)} - \frac{0.486}{\left(1+\exp\left(\frac{-(t-89.512)}{7.885}\right)\right)}\right) \qquad (39)$$

$$\phi_t = \phi_o\left(1 + \frac{0.1274}{\left(1+\exp\left(\frac{-(t-49.373)}{8.447}\right)\right)} - \frac{0.1274}{\left(1+\exp\left(\frac{-(t-89.512)}{7.885}\right)\right)}\right) \qquad (40)$$

$$\forall\ t \in t \geq t_s;\ t_s = 14, N_o = 30000, \phi_o = 0.887$$

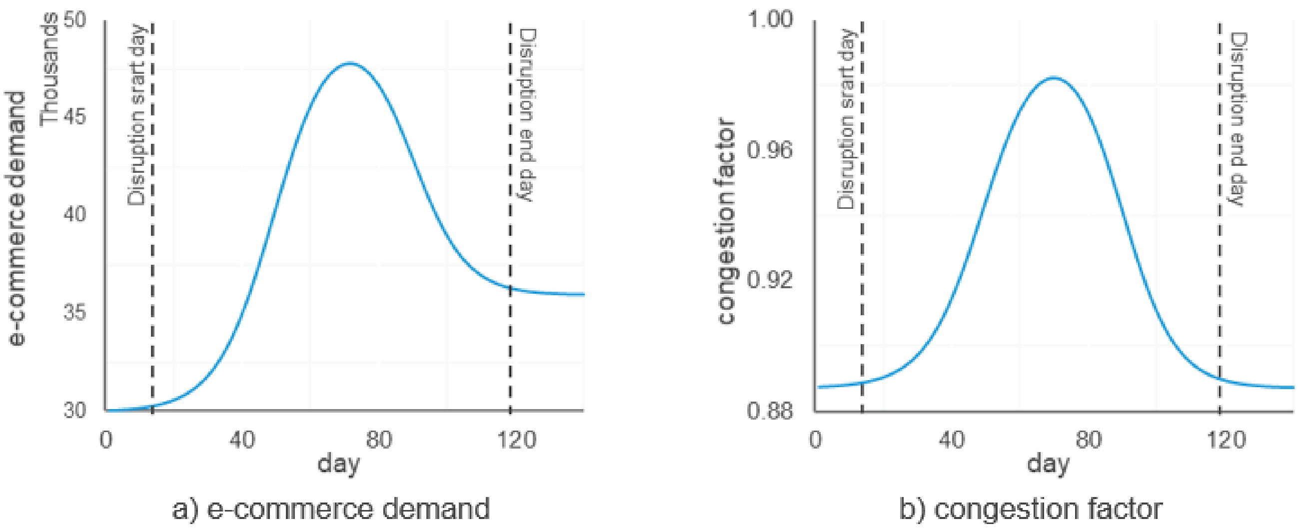



**Figure 6. Modeled market disruption instigated by the COVID-19 pandemic**

## Detailing last-mile distribution operations under the COVID-19 disruption:

### Without outsourcing

Due to lean management practices, the e-retailer's distribution structure has little slack capacity (Figure 7). The e-retailer thus continues to serve ~30k customers daily while completely dropping more than a 5$^{th}$ of all demand in the peri-disruption stage. This renders an out-of-pocket distribution cost of ~$50.35k (equivalent to $1.68 per package; Figure 8) but also an unobserved cost of unmet demand to the e-retailer. Thus, to cope with this surge in demand, the e-retailer could outsource part of its operations via the outsourcing channels while delaying delivery for excess demand beyond the combined distribution capacity.

### With delivery via crowdsourced fleet

Last-mile delivery via a fleet of crowdsourced vehicles offers one such outsourcing option. This crowdsourced fleet operates independently of the e-retailer's distribution channel as the crowdsourced drivers collect packages from the e-commerce fulfillment facility before embarking on a delivery tour. Hence, crowdsourcing delivery renders flexible and on-demand deployment, with the e-retailer catering to 30k customers using its fleet of class-5 diesel trucks and outsourcing the remaining via the crowdsourced fleet. Altogether, the 565 crowdsourced light duty trucks, each with a capacity to serve 30 customers in a delivery tour, augment the distribution capacity by 16.95k customers, taking it to ~47.9k customers, which is sufficient to serve the peak disruption demand of 47.8k customers (Figure 7). Thus, as the demand rises in the peri-disruption stage, the e-retailer gradually employs more crowdsourced drivers for last-mile deliveries on an on-demand basis, with at most 35.2% packages crowdsourced at peak disruption, resulting in a distribution cost of $82.97k, equivalent to $1.74 per package (Figure 8). In the post-disruption stage on the other hand, the e-retailer observes a daily demand of 36k customers, of which the e-retailer serves 30k customers using its fleet of diesel trucks and crowdsources deliveries for the remaining 6k customers (16.6% packages), with a total distribution cost of $1.76 per package.

These results showcase the flexibility of crowdsourced last-mile deliveries in coping with a surge in demand. However, it is important to note that the effectiveness of a crowdsourced service is sensitive to the availability of drivers willing to deliver packages. Thus, to ensure reliable last-mile operations, the e-retailer can offer better incentives to crowdsource, whether with higher hourly remuneration, reimbursement of maintenance and fuel costs, and/or a start-on bonus. Nonetheless, delivery via a crowdsourced fleet can be challenging, more so in the context of the COVID-19 pandemic, wherein virus containment measures such as stay-at-home orders inhibit public movement and may further limit the availability of crowdsourced drivers.

### With customer pickup at collection-points

Alternatively, the e-retailer can outsource the last-mile to the customer through pickups at collection-points. However, unlike with crowdsourced deliveries, outsourcing via collection-points is dependent on the e-retailer's distribution channel. In particular, the e-retailer must fulfill the collection-points before customers can collect their packages. Thus, as the demand rises in the peri-disruption stage, the e-retailer gradually loads its underutilized delivery trucks with additional packages (recall, 85% load utilization in pre-disruption), which are eventually unloaded at collection-points for customer pickup. This demand consolidation at collection-points, along with the reduced traffic congestion in the peri-disruption stage, enables the e-retailer to continue complying with driver working-hours despite loading its delivery trucks with more packages. As the demand rises to 35.28k customers, the delivery trucks reach full-truckload with a large share of packages consolidated for collection-point pickup. As the demand further surges beyond this level, the delivery trucks make an additional delivery tour to cater to this increased demand, adding non-negotiable long-haul travel time, and therefore, to comply with driver working-hours, the e-retailer reduces delivery trucks' time spent traveling in the last-mile by outsourcing and consolidating an even larger share of packages for collection-point pick-up. This is evident by the sharp jump in distribution costs depicted in Figure 8. Thus, at peak disruption, the e-retailer consolidates 84% of packages for collection-point pickup, resulting in a distribution cost of $73.24k, equivalent to $1.53 per package (Figure 8). In the post-disruption stage then, the e-retailer observes a daily demand of 36k customers, beyond the 35.28k customer threshold, and therefore continues to operate and depend heavily on the outsourcing channel, delivering 83.7% of all its packages via collection-points at a distribution cost of $1.79 per package. At this point, the e-retailer can acquire 2 additional class-5 diesel trucks to increase the volume capacity of its fleet to 36k and thereby reduce its dependence on the outsourcing channel with only as much as 26.7% of the total demand routed for collection-point pick-up, resulting in a distribution cost of $1.61 per package. Alternatively, the e-retailer can purchase 19 additional class-5 diesel trucks and completely eliminate the use of this outsourcing channel for a distribution cost of $1.59 per package.

While these results present the cost-effectiveness of collection-points to cope with a surge in demand, the success of collection-points is nonetheless contingent on the willingness of customers to collect their packages. In fact, in the context of the COVID-19 pandemic, customer's willingness to self-collect a package could be sensitive to the individual's perceived susceptibility to the virus. Moreover, it is important to account for the increased externalities, i.e., vehicle miles traveled and emissions from individuals traveling to collect packages at collection-points, when discussing the use of collection-points in general.

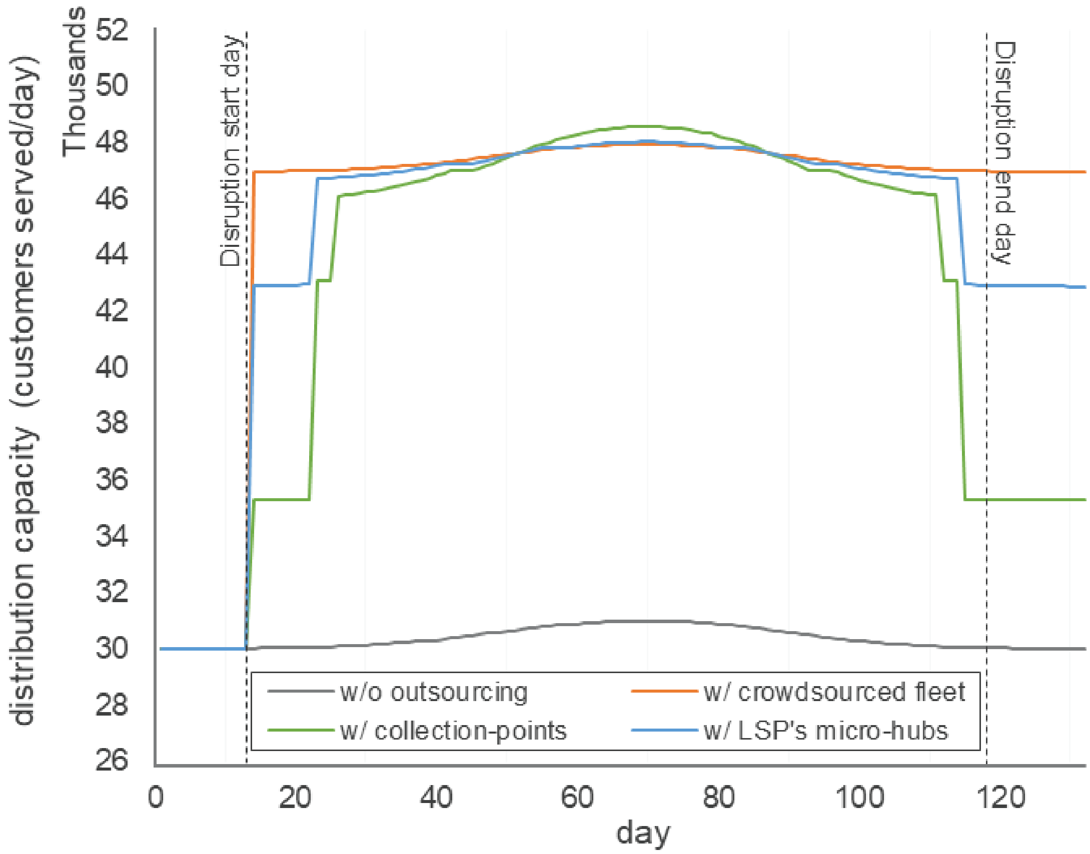



**Figure 7. Distribution capacity with/without outsourcing**

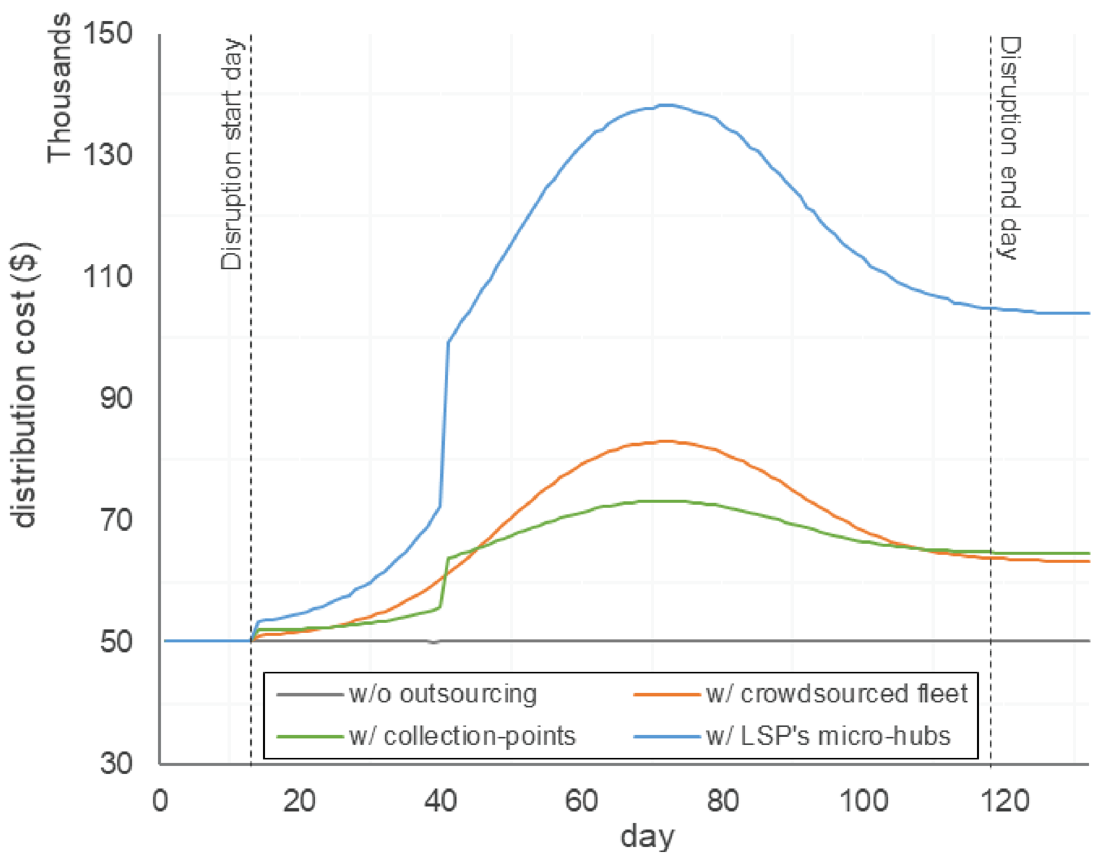



**Figure 8. Distribution cost with/without outsourcing**

### With distribution via micro-hubs using cargo-bikes operated by the logistics service provider (LSP)

Similar to collection-points, outsourcing via micro-hubs requires that the e-retailer fulfill the micro-hubs before the LSP's cargo-bikes can embark for last-mile deliveries. Thus, in the peri-disruption stage, as the demand rises, the e-retailer gradually loads its delivery trucks with additional packages consolidated for the LSP to distribute. In doing so, the e-retailer complies with the driver working-hours until the demand surges beyond the 35.28k customer threshold. To cater to the demand beyond this threshold, the delivery trucks make an additional delivery tour, adding non-negotiable long-haul travel time. At this point, to comply with driver working-hours, the e-retailer reduces the time spent by the delivery trucks traveling in the last-mile by consolidating a much larger share of packages for distribution via the LSP. This again is evident by the sharp jump in distribution cost depicted in Figure 8. Thus, at peak disruption, the e-retailer consolidates 82.1% of packages for distribution via the LSP, resulting in a distribution cost of $138.1k, equivalent to $2.89 per package (Figure 8). In the post-disruption stage then, the e-retailer observes a daily demand of 36k customers, yet still beyond the 35.28k customer threshold. To cater to this post-disruption demand, the e-retailer routes as much as 59.2% of its packages via the LSP, amounting to a distribution cost of $2.88 per package. As with the collection-points, at this stage the e-retailer can acquire 2 additional class-5 diesel trucks, which increases the volume capacity of its fleet to 36k and thereby reduces its dependence on the outsourcing channel with only as much as 26.2% of the total demand distributed via the LSP, resulting in a distribution cost of $2.10 per package. Alternatively, the e-retailer can purchase 19 additional class-5 diesel trucks and completely eliminate the use of outsourcing channels for a distribution cost of $1.59 per package.

It is important to note that the LSP could itself be constrained for resources due to the disruption, nonetheless, the results highlight the need for prior contracts with multiple such logistics service providers to efficiently reroute distribution in the event of disruptions. Moreover, unlike either of the two previously discussed outsourcing channels, outsourcing via a third-party LSP offers the least potential for uncertainty in the distribution process.

## Evaluating e-retailer's performance under the COVID-19 disruption

The results developed above, and the related discussion offer salient insight into the last-mile distribution operations of the e-retailer using different outsourcing channels under the market disruption instigated by the COVID-19 pandemic. Recall, we designed the outsourcing channels and planned the available resources such that the e-retailer can just about serve the increased demand, thereby rendering resilient last-mile distributions with the e-retailer operating at a full level of service. However, to assess the capability of the e-retailer's distribution operations to maintain and efficiently restore level of service under the same pandemic-instigated market disruption, we assume the outsourcing channels to be resource constrained and therefore limit the share of packages they can service, implicitly or explicitly, in the form of a (maximum) permissible outsourcing share ($p_u$). For instance, a crowdsourced fleet implicitly limits the number of customers it can deliver to in the form of driver availability, while customer willingness to self-collect package indicates the share of packages that the e-retailer can deliver via collection-point for customer pickup, and the LSP can explicitly express the maximum share of packages it is willing to distribute considering its own internal resource constraints. Such constraints effectively limit the distribution capacity and force the e-retailer to operate at a lower level of service. Note, below a certain permissible level of outsourcing share, the e-retailer's distribution capacity would fall short of the post-disruption demand of 36k customers, resulting in last-mile distributions at a near zero level of service after the disruption. On the other hand, above a certain permissible level of outsourcing share, the e-retailer can have sufficiently large distribution capacity, enough to serve the peak peri-disruption demand of 47.8k customers, thereby enabling last-mile distribution at a full level of service. The discussion hereon assesses the performance of the e-retailer constrained for the values of maximum permissible outsourcing share between the two thresholds under the COVID-19 instigated disruption (see Table 2).

**Table 2. Lower and upper threshold for permissible outsourcing share**

| Outsourcing | Lower threshold | Upper threshold |
|---|---|---|
| w/ crowdsourced fleet | 0.167 | 0.352 |
| w/ collection-points | 0.600 | 0.836 |
| w/ LSP's micro-hubs | 0.595 | 0.820 |

The analysis employs resilience metrics to evaluate robustness, redundancy, resourcefulness, and rapidity of the e-retailer's level of service; operational metrics to evaluate total and average delay; and economic metrics to measure direct, indirect, and total loss. The resilience metrics of robustness and redundancy reflect the magnitude and rate of loss in the e-retailer's level of service, while resourcefulness and rapidity assess the magnitude and rate of recovery, respectively. The operational metrics characterize the delay in service, in particular, the total delay expresses cumulative delay in terms of number of package-days of delayed service, while the average delay evaluates the average number of additional packages delayed on any day, and the average number of days a package is delayed, assuming that packages are delivered on a first-come-first-served basis. The economic metrics, namely direct loss, evaluates the change in distribution cost relative to pre-disruption distribution cost ($50.35k), and indirect loss accounts for the loss from delayed service penalizing late delivery at $5 per package for every day of delayed service, while the total loss is simply the sum of direct and indirect loss, and thereby reflects the explicit and implicit costs to the e-retailer.

To begin, a permissible outsourcing share beyond the lower threshold renders distribution capacity that functions as slack capacity as the disruption fades away, thus enabling the e-retailer to restore the level of service and limit the disruption loss. In fact, an increase in permissible outsourcing share increases the distribution capacity which: increases the slack capacity building robustness and redundancy, enables faster recovery improving rapidity, and reduces service delays limiting the disruption loss to the e-retailers. Resourcefulness remains constant at 1.0 since any amount of slack capacity ensures recovery. These dynamics are evident in Figure 9, Figure 10, and Figure 11, which highlight the variation in resilience, operational, and economic metrics, respectively, for last-mile distribution operations with the e-retailer outsourcing distribution via the LSP constrained to a maximum permissible outsourcing share in the range of 0.60 to 0.82. Further, Table 3, Table 4, and Table 5 quantify these dynamics in the form of resilience elasticity, operational sensitivity, and economic sensitivity, respectively. Note, elasticity measures the % change in the value for a % increase in permissible outsourcing share, while sensitivity measures the absolute change in the value for a % increase in permissible outsourcing share. For instance, a % increase in customer's willingness to self-collect package from a collection-point increases the distribution slack capacity, rendering a 7.4% improvement in robustness, a 2.9% improvement in redundancy, and a 9.5% improvement in the rapidity of last-mile distribution operations, with reduction in shipping time by 16 days resulting in a $3.2b lower disruption loss to the e-retailer. Similarly, a 2.8% increase in number of drivers available for crowdsourcing (or a % increase in permissible outsourcing share) increases the slack capacity, improving robustness by 3.6%, redundancy by 1.7%, and rapidity by 3.2%, with on average 6k fewer packages delayed per day, resulting in a $0.7b lower disruption loss to the e-retailer.

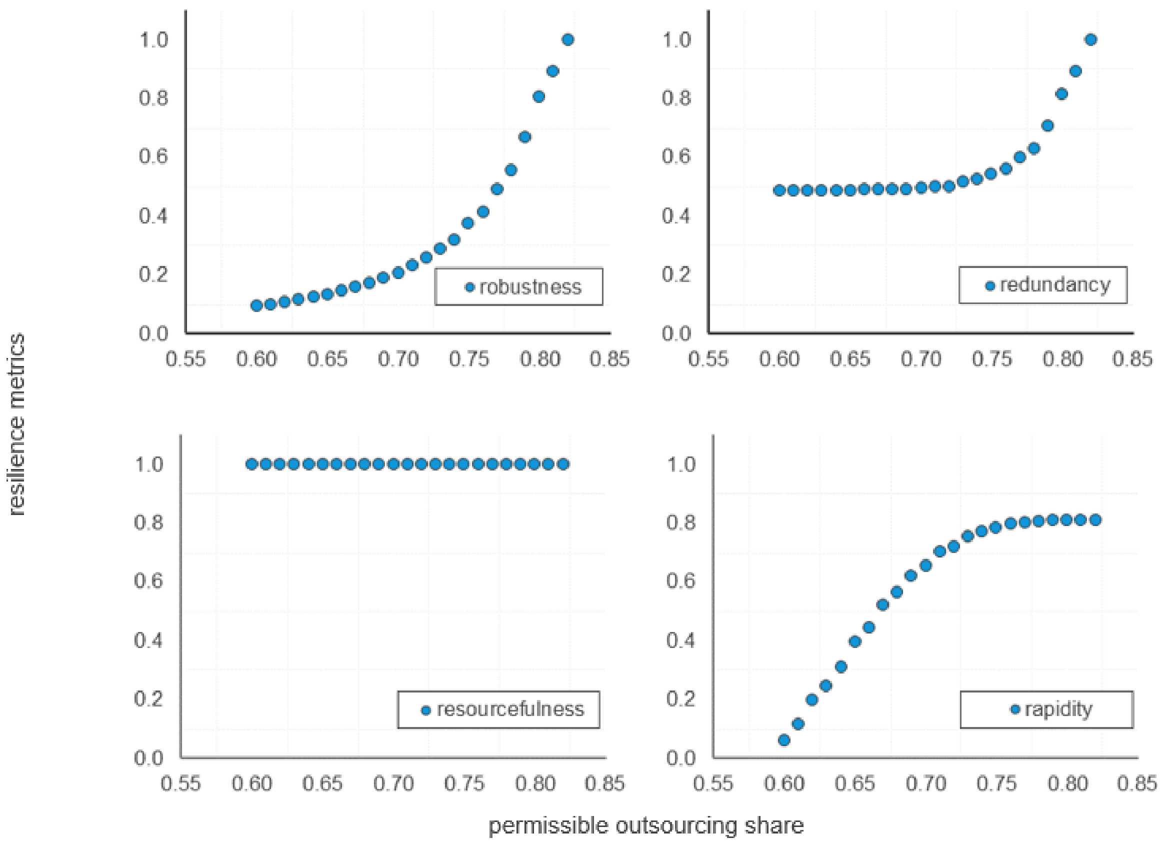



**Figure 9. Resilience dynamics of last-mile distribution (outsourcing via LSP)**

**Table 3. Resilience metric elasticity with respect to permissible outsourcing share**

| Outsourcing | Robustness | Redundancy | Resourcefulness | Rapidity |
|---|---|---|---|---|
| w/ crowdsourced fleet | 3.592 | 1.700 | 0.000 | 3.207 |
| w/ collection-points | 7.374 | 2.877 | 0.000 | 9.487 |
| w/ LSP's micro-hubs | 7.626 | 3.218 | 0.000 | 8.475 |

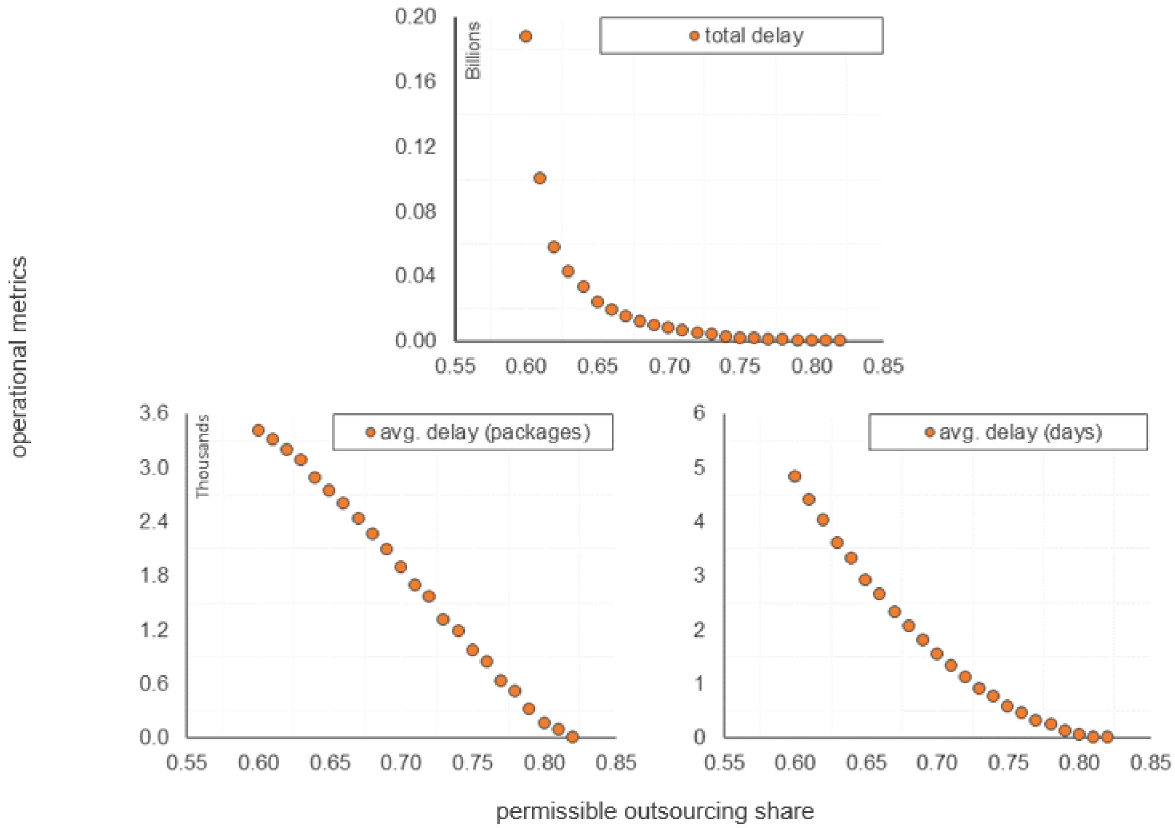



**Figure 10. Operational dynamics of last-mile distribution (outsourcing via LSP)**

These tables also highlight the differences between the different outsourcing channels. For instance, Table 3 shows the improvement in last-mile distribution resilience with crowdsourced delivery to be relatively modest in comparison to the other two outsourcing channels. Because every crowdsourced driver only makes one delivery tour given the incentives on offer, the increase in distribution capacity is only marginal as more crowdsourced drivers are employed. In fact, a 1% increase in permissible outsourcing share renders only 132m fewer package delays (~$0.67b fewer losses) for last-mile distribution with packages outsourced for crowdsourced delivery, in contrast to 322m fewer package delays (~$1.69b fewer losses) with packages outsourced for distribution via the LSP, and 628m fewer package delays (~$3.19b fewer losses) with packages outsourced for customer pickup at collection-points (see Table 4). However, the differences in direct loss sensitivity are contingent on the cost structure. In particular, operating a crowdsourced fleet with drivers remunerated only for hourly wages renders significantly low last-mile operational costs; similarly, customer pickup from collection-points saves the e-retailer on last-mile operational costs for its fleet of delivery trucks, whereas the LSP charges high operational costs in the form of hourly driver wages, as well as cargo-bike energy and maintenance costs. Hence, a 1% reduction in permissible outsourcing share limits consolidation benefits (economy of scale benefits) for the outsourcing channel, rendering as much as a $81.4m increase in direct loss for last-mile distributions with packages outsourced for distribution via the LSP in contrast to a $46.8m increase with packages outsourced for collection-point pickup, and only a $17.4m increase with packages outsourced for crowdsourced delivery (see Table 5). While the cost structure employed in this work is consistent with real-world examples, it is important to note that modeling certain parameters is outside the scope of this work, such as crowdsourced driver availability as a function of delivery incentives, customer willingness to self-collect considering their value of time, and the cooperation and collaboration dynamics between the e-retailer and the logistics service provider.

**Table 4. Operational metric sensitivity with respect to permissible outsourcing share**

| Outsourcing | Total delay (billion package-days) | Average delay (thousand packages) | Average delay (days) |
|---|---|---|---|
| w/ crowdsourced fleet | -0.132 | -6.014 | -7.849 |
| w/ collection-points | -0.628 | -11.79 | -15.76 |
| w/ LSP’s micro-hubs | -0.322 | -11.71 | -15.61 |

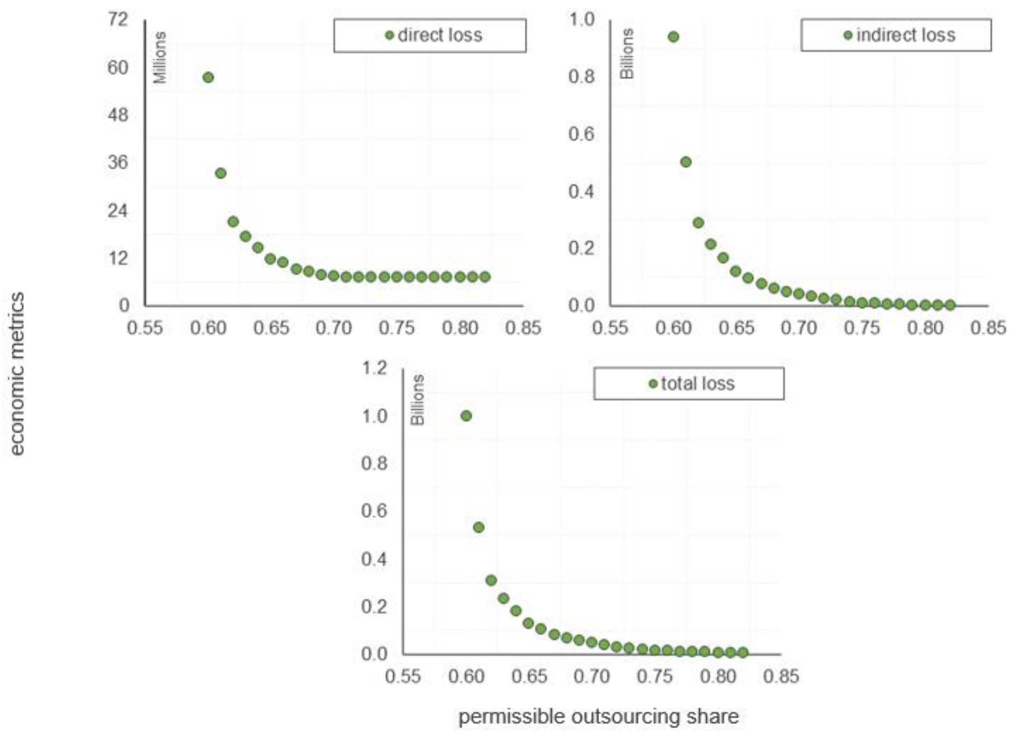



**Figure 11. Economic dynamics of last-mile distribution (outsourcing via LSP)**

**Table 5. Economic metric sensitivity with respect to permissible outsourcing share**

| Outsourcing | Direct loss (m$) | Indirect loss (b$) | Total loss (b$) |
|---|---|---|---|
| w/ crowdsourced fleet | -17.37 | -0.660 | -0.677 |
| w/ collection-points | -46.83 | -3.138 | -3.185 |
| w/ LSP's micro-hubs | -81.36 | -1.611 | -1.692 |

## Sensitivity analysis - market disruptions (in general) with varying characteristics

Having assessed the e-retailer's response to the market disruption that ensued with the COVID-19 pandemic, we assess the e-retailer's performance under disruptions in general in this subsection. This market disruption triggers a generalized increase in e-commerce demand and a generalized reduction in traffic congestion, as modeled in *Equation (41) and (42)*, respectively. The analysis here performs sensitivity analysis by varying disruption characteristics—growth/decay factor (% increase to/from peak disruption), growth/decay half-life (days to half the increase/decrease to/from peak disruption), and inverse growth/decay rate (inverse of the rate of increase/decrease to/from peak disruption)—and in turn assesses the e-retailer's performance gauging the resilience, operational, and economic metrics of its last-mile distribution. Again, much like in the previous subsection, the sensitivity analysis here varies the disruption characteristics such that the e-retailer has enough distribution capacity to serve the post-disruption demand but not enough to serve the peak peri-disruption demand. This allows for an analysis of the e-retailer's operations at a reduced level of service, albeit with the e-retailer having enough resources to restore and recover to full level of service. Table 6 lists the range of values of the distribution characteristics employed in this sensitivity analysis, with Table 7, Table 8, and Table 9 presenting the resilience elasticity, operational sensitivity, and economic sensitivity, respectively, in this range.

$$N_t = N_o\left(1 + \frac{\alpha_1}{\left(1 + \exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)\right)} - \frac{\alpha_2}{\left(1 + \exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)\right)}\right) \tag{41}$$

$$\phi_t = \phi_o\left(1 + \frac{\alpha}{\left(1 + \exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)\right)} - \frac{\alpha}{\left(1 + \exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)\right)}\right) \tag{42}$$

$$\forall\ t \geq t_s;\ N_o = 30{,}000,\ \phi_o = 0.887$$

To begin, an increase in the value of two of the six disruption characteristics, growth factor and decay half-life, and a decrease in the value of the other four disruption characteristics, results in an effective increase in the severity of the disruption. This then results in a reduction in the robustness and redundancy of last-mile distributions, but also increases rapidity, highlighting the elastic nature of the last-mile response to disruption

(Table 7). The elasticity of resourcefulness with respect to the disruption characteristics is zero, since any amount of slack capacity enables the e-retailer to service delayed demand and thereby to restore the level of service, as discussed before. Concomitantly, this increase in disruption severity renders an increase in direct loss and also an increase in indirect loss owing to the increased amount of package delays (Table 8), thereby increasing the total loss from disruption for the e-retailer (Table 9). For instance, for an e-retailer outsourcing last-mile to the customers for pickup at collection-points, a 1% increase in growth factor increases disruption severity rendering an additional ~4.1k packages delayed on average every day which results in a 4.5% reduction in robustness, a 3.0% reduction in redundancy, and $48.3m more in total loss from the disruption. On the other hand, for this e-retailer, a 1% decrease in decay rate (or a 1% increase in inverse decay rate) reduces disruption severity, resulting in 0.24m fewer package delays, which renders a 0.15% increase in robustness, a 0.11% increase in redundancy, a 0.57% reduction in rapidity, and $1.07m fewer losses from disruption.

**Table 6. Range of values of distribution characteristics for sensitivity analysis**

| Distribution characteristics | Lower threshold | Upper threshold |
|---|---|---|
| **Growth factor - $\alpha_1$** | | |
| w/ crowdsourced fleet | 0.685 | 1.000 |
| w/ collection-points | 0.710 | 0.840 |
| w/ LSP's micro-hubs | 0.700 | 0.900 |
| **Growth half-life - $\mu_1$** | | |
| w/ crowdsourced fleet | 37 | 48 |
| w/ collection-points | 37 | 42 |
| w/ LSP's micro-hubs | 37 | 48 |
| **Inverse growth rate - $\theta_1$** | | |
| w/ crowdsourced fleet | 0.5 | 8.0 |
| w/ collection-points | 0.4 | 6.0 |
| w/ LSP's micro-hubs | 0.5 | 8.0 |
| **Decay factor - $\alpha_2$** | | |
| w/ crowdsourced fleet | 0.100 | 0.425 |
| w/ collection-points | 0.180 | 0.270 |
| w/ LSP's micro-hubs | 0.260 | 0.400 |
| **Decay half-life - $\mu_2$** | | |
| w/ crowdsourced fleet | 95 | 150 |
| w/ collection-points | 95 | 150 |
| w/ LSP's micro-hubs | 95 | 150 |
| **Inverse growth rate - $\theta_2$** | | |
| w/ crowdsourced fleet | 0.5 | 7.5 |
| w/ collection-points | 0.3 | 5.1 |
| w/ LSP's micro-hubs | 0.5 | 7.5 |

These results can help inform the e-retailer's decision-making in the event of similar future disruptions. In particular, the elasticity of robustness with respect to disruption severity (Table 7) shows last-mile distribution with packages outsourced for customer pickup from collection-points to be the least sensitive channel to the severity of the disruption, rendering operations resilient despite its dependence on the e-retailer for fulfillment. In comparison, outsourcing distribution with an LSP is more sensitive to the severity of disruption, and crowdsourced delivery is even more sensitive. Noting the magnitude of operational sensitivity across the three outsourcing channels (Table 8), again, the results indicate that last-mile distribution with crowdsourced deliveries is the most sensitive to the severity of disruption, followed by distribution with an LSP, while customer pickup at collection-points is least sensitive to disruption severity.

**Table 7. Resilience elasticity to disruption characteristics**

| Resilience elasticity | | Robustness | Redundancy | Resourcefulness | Rapidity |
|---|---|---|---|---|---|
| **w/ crowdsourced fleet** | | | | | |
| Growth factor | $\alpha_1$ | -5.088 | -2.054 | 0.000 | 0.000 |
| Decay factor | $\alpha_2$ | 0.273 | 0.122 | 0.000 | 0.000 |
| Growth half-life | $\mu_1$ | 0.978 | 0.649 | 0.000 | -1.572 |
| Decay half-life | $\mu_2$ | -2.616 | -0.914 | 0.000 | 1.527 |
| Inv. growth rate | $\theta_1$ | 0.306 | 0.228 | 0.000 | -0.325 |
| Inv. decay rate | $\theta_2$ | 0.246 | 0.155 | 0.000 | -0.397 |
| **w/ collection-points** | | | | | |
| Growth factor | $\alpha_1$ | -4.475 | -3.022 | 0.000 | 7.383 |
| Decay factor | $\alpha_2$ | 0.168 | 0.089 | 0.000 | 0.000 |
| Growth half-life | $\mu_1$ | 0.465 | 0.253 | 0.000 | -1.429 |
| Decay half-life | $\mu_2$ | -1.830 | -0.855 | 0.000 | 2.082 |
| Inv. growth rate | $\theta_1$ | 0.201 | 0.172 | 0.000 | -0.513 |
| Inv. decay rate | $\theta_2$ | 0.150 | 0.105 | 0.000 | -0.569 |
| **w/ LSP** | | | | | |
| Growth factor | $\alpha_1$ | -5.053 | -2.612 | 0.000 | 0.000 |
| Decay factor | $\alpha_2$ | 0.113 | 0.000 | 0.000 | 0.000 |
| Growth half-life | $\mu_1$ | 0.829 | 0.595 | 0.000 | -1.825 |
| Decay half-life | $\mu_2$ | -2.460 | -0.924 | 0.000 | 1.774 |
| Inv. growth rate | $\theta_1$ | 0.283 | 0.223 | 0.000 | -0.383 |
| Inv. decay rate | $\theta_2$ | 0.224 | 0.150 | 0.000 | -0.445 |

All results here are statistically significant with 95% confidence

These trends in turn reflect the indirect loss sensitivity for the three outsourcing channels. A 1% increase in growth factor renders a $46.2m increase in indirect monetary losses to the e-retailer for last-mile distribution with packages outsourced for collection-point pickup, in contrast to a $154.7 increase with packages outsourced for distribution via an LSP, and as much as a $229.7m increase with packages outsourced for crowdsourced deliveries. However, outsourcing last-mile distribution operations to an LSP results in a substantial direct loss to the e-retailer, owing to the high operational costs of distribution, with as much as a $30.5m increase in direct loss for a 1% increase in growth factor, in contrast to a $9.95m increase with packages outsourced for crowdsourced delivery, and only a $2.93m increase with packages outsourced for collection-point pickup. Recall that at peak disruption, the e-retailer could operate at a full level of service for a total cost of $2.89 per package with distribution outsourced to an LSP, in contrast to $1.74 with crowdsourced delivery, and $1.53 with packages outsourced for collection-point pickup. Nonetheless, operations with a crowdsourced fleet or with collection-points are susceptible to the willingness of stakeholders, drivers, and customers, to engage in the distribution process, while distribution via an LSP is not constrained by such uncertainties.

**Table 8. Operational sensitivity to disruption characteristics**

| Operational sensitivity | | Total delay (million package-days) | Average delay (thousand packages) | Average delay (days) |
|---|---|---|---|---|
| **w/ crowdsourced fleet** | | | | |
| Growth factor | $\alpha_1$ | 45.93 | 7.132 | 5.741 |
| Decay factor | $\alpha_2$ | 0.000 | -0.245 | -0.242 |
| Growth half-life | $\mu_1$ | -6.904 | -1.108 | -0.828 |
| Decay half-life | $\mu_2$ | 9.796 | 2.204 | 2.036 |
| Inv. growth rate | $\theta_1$ | 0.000 | -0.340 | -0.219 |
| Inv. decay rate | $\theta_2$ | 0.000 | -0.236 | -0.126 |
| **w/ collection-points** | | | | |
| Growth factor | $\alpha_1$ | 9.244 | 4.163 | 2.222 |
| Decay factor | $\alpha_2$ | -0.466 | -0.135 | -0.094 |
| Growth half-life | $\mu_1$ | -1.448 | -0.423 | -0.289 |
| Decay half-life | $\mu_2$ | 5.593 | 1.258 | 0.986 |
| Inv. growth rate | $\theta_1$ | -0.383 | -0.188 | -0.101 |
| Inv. decay rate | $\theta_2$ | -0.241 | -0.120 | -0.053 |
| **w/ LSP** | | | | |
| Growth factor | $\alpha_1$ | 30.94 | 5.947 | 3.763 |
| Decay factor | $\alpha_2$ | 0.000 | -0.146 | -0.152 |
| Growth half-life | $\mu_1$ | -6.428 | -0.849 | -0.524 |
| Decay half-life | $\mu_2$ | 8.150 | 1.955 | 1.722 |
| Inv. growth rate | $\theta_1$ | 0.000 | -0.295 | -0.171 |
| Inv. decay rate | $\theta_2$ | 0.000 | -0.199 | -0.088 |

All results here are statistically significant with 95% confidence

Considering the opportunities and challenges associated with the different outsourcing channels, the e-retailer must carry out appropriate pre-disruption planning to ensure sufficiently robust, redundant, resourceful and rapid last-mile distribution at reasonable costs (direct and indirect loss). The e-retailer can do this: (i) by creating a suitable platform and providing adequate incentives to establish reliable crowdsourced deliveries, especially to cope with low severity disruptions; (ii) by negotiating contracts with several LSPs to deploy backup distribution, especially for moderately severe disruptions; and (iii) by establishing a sufficient number of lockers and enough collection-points near customers' residential and workplace areas to ensure customer willingness to self-collect packages, particularly to cope with high severity disruptions. The e-retailer must also gauge the disruption as it evolves in different phases and appropriately re-evaluate the incentives offered for crowdsourced service, the use of collection-points and lockers for customer pickup, and the need for backup last-mile distribution.

**Table 9. Economic sensitivity to disruption characteristics**

| Economic sensitivity | | Direct loss (m$) | Indirect loss (m$) | Total loss (m$) |
|---|---|---|---|---|
| **w/ crowdsourced fleet** | | | | |
| Growth factor | $\alpha_1$ | 9.946 | 229.7 | 238.3 |
| Decay factor | $\alpha_2$ | -2.300 | 0.000 | 0.000 |
| Growth half-life | $\mu_1$ | -4.192 | -34.52 | -37.08 |
| Decay half-life | $\mu_2$ | 4.507 | 48.98 | 52.41 |
| Inv. growth rate | $\theta_1$ | 0.000 | 0.000 | 0.000 |
| Inv. decay rate | $\theta_2$ | 0.000 | 0.000 | 0.000 |
| **w/ collection-points** | | | | |
| Growth factor | $\alpha_1$ | 2.927 | 46.22 | 48.34 |
| Decay factor | $\alpha_2$ | -0.326 | -2.331 | -2.566 |
| Growth half-life | $\mu_1$ | -2.587 | -7.238 | -8.591 |
| Decay half-life | $\mu_2$ | 2.776 | 27.97 | 30.94 |
| Inv. growth rate | $\theta_1$ | -0.055 | -1.913 | -1.911 |
| Inv. decay rate | $\theta_2$ | 0.081 | -1.207 | -1.074 |
| **w/ LSP** | | | | |
| Growth factor | $\alpha_1$ | 30.47 | 154.7 | 182.9 |
| Decay factor | $\alpha_2$ | -3.850 | 0.000 | 0.000 |
| Growth half-life | $\mu_1$ | -10.19 | -32.14 | -40.25 |
| Decay half-life | $\mu_2$ | 12.24 | 40.75 | 51.71 |
| Inv. growth rate | $\theta_1$ | 0.000 | 0.000 | 0.000 |
| Inv. decay rate | $\theta_2$ | 0.000 | 0.000 | 0.000 |

All results here are statistically significant with 95% confidence

# Discussion and Conclusions

In the years prior to the COVID-19 pandemic, consumer shopping trends had seen a steady and significant shift towards online retail. Despite the prevalence of e-commerce platforms with lucrative shopping offers for consumers, traditional in-store shopping still dominated daily consumer purchases. Nonetheless, more and more consumers had been engaging in omnichannel behavior, with product search, trial, and final purchase occurring in different channels. However, the COVID-19 pandemic significantly inhibited public movement, and an unprecedented number of consumers, including many first-time users, took to e-commerce platforms for the purchase of critical goods, daily essentials, groceries, medications, and health-care products. Beyond the typical B2C services, some e-retailers also delivered personal protective equipment, including gowns, masks, and gloves to frontline healthcare workers and hospitals. Typically, these e-retailers account for only minor day-to-day and seasonal disruptions and thereby design their distribution structures for low-cost just-in-time deliveries, leaving the supply-chain vulnerable to such severe and unforeseen disruptions. Given the role of e-retailers in maintaining the supply of essential goods not only to the typical customer but also to frontline services, in this study, we assessed last-mile distribution resilience in terms of an e-retailer's ability to maintain and efficiently restore level of service in the event of such a low-probability high-severity disruption. Research on low-probability high-severity disruptions in the context of transportation, however, is limited to disaster management, humanitarian logistics, and relief operations for earthquakes, tsunamis, hurricanes, terrorist attacks, etc. (*67*). However, the total breakdown of global supply-chains and the consequent surge in e-commerce demand for months after the initial COVID-19 outbreak was unlike any other low-probability high-severity disruption, and therefore warrants dedicated research.

This work assumes that, to cope with such disruptions, the e-retailer outsources part of its operations via different outsourcing channels, namely, with crowdsourced fleet of light-duty trucks, collection-points for customer pickup (lockers), or via a LSP operating from micro-hubs using a fleet of electric cargo-bikes. The results of this study highlight the opportunities and challenges associated with these channels, in particular, the flexible service contingent on driver availability afforded by an independent crowdsourced fleet, the unconstrained downstream capacity contingent on customer willingness to self-collect packages at collection-points, and the reliable service of an LSP, at the expense of high distribution costs. Considering the opportunities and challenges associated with the different outsourcing channels, it could be useful to establish crowdsourced deliveries to cope with low severity disruptions, deploy backup distribution for moderately severe disruptions, and encourage customers to self-collect packages to cope with high severity disruptions. Nonetheless, the e-retailer must carry out appropriate pre-disruption planning to create suitable platforms and incentives to ensure reliable crowdsourced deliveries, position sufficient number of lockers near residential areas to ensure customer willingness to self-collect packages, and negotiate contracts with several LSPs to ensure backup last-mile distribution. Moreover, as the disruption evolves, the e-retailer must gauge the availability of crowdsourced drivers, the willingness of customers to self-collect packages, and the capability of the LSPs to ensure the function of its distribution channel, so that the e-retailer can deploy the appropriate outsourcing channel(s) during the different phases of the disruption. Finally, as the disruption recedes, the e-retailer must re-engage strategic and tactical decision-making processes not only to restore the level of service efficiently and in a timely manner, but also to plan ahead for a changed post-disruption landscape. Moreover, the e-retailer must consider equity implications for its staff, workers, and drivers in order to ensure a safe working environment and prevent any job hazards not only under business-as-usual conditions, but with special protocols for each phase of the disruption. Equally, the e-retailer and the regulatory bodies must consider general equity implications of last-mile distributions in terms of exposure to freight related externalities, home-based accessibility to last-mile delivery services, etc. *(68)*. Thus, consistent with other studies in the resilience literature, this study highlights the need for organizational, social, economic, and engineering units of last-mile distribution to consistently perform pre-disruption mitigation, appropriately respond during the disruption, and efficiently carry out post-disruption analysis and recovery for last-mile distribution to be resilient to disruption.

With this study, we developed a holistic understanding concerning the capability of e-retailers' last-mile distribution operations to maintain and efficiently restore service levels under disruption. In particular, we integrated the R4 resilience framework (*3*) and the resilience triangle concept (*2*), thus developing the R4 Resilience Triangle Framework to assess the resilience of an e-retailer's last mile distribution operations developed using Continuous Approximation (CA) techniques. This novel resilience framework quantifies the qualitative properties of resilience, i.e., robustness, redundancy, resourcefulness, and rapidity using the resilience triangle, thereby characterizing the drop in performance of the system due to the disruption. Moreover, the domain-agnostic nature of this resilience framework enables assessment of a system's response to disruption not only in the context of transportation systems, but across varying domains. However, we also acknowledge the key limitations of this study, in particular the study does not account for: (i) the availability of drivers for crowdsourced operations, or the impact of incentives to ensure the consistent availability of drivers willing to crowdsource; (ii) unobserved costs besides those from delayed service, such as the customer's value of time traveling to collect packages from the collection-points and the impact of those costs on customers' willingness to self-collect packages; and (iii) some second- order disruption effects (other than reduced traffic congestion and increased distribution capacity) that could inhibit distribution capacity, such as the unavailability of human resources both for the e-retailer and for the logistics service providers. Nonetheless, the analyses performed in this study present robust results that can guide e-retailers' decision-making in the event of future disruptions to maintain and efficiently restore last-mile distribution level of service.

Importantly, this work highlights the need to develop not only sustainable last-mile distribution structure that can render economically viable, environmentally friendly, and socially equitable operations capable to cope with high-probability low-severity fluctuations in the delivery environment, but also resilient last-mile distribution structure that is robust, redundant, resourceful, and rapid against low-probability high-severity disruptions. Consistent with the suggestions from Esmalian et al. (*69)* and Kurth et al. (*70)*, future work must develop last-mile distribution structure with such a holistic outlook of system design to ensure sustainable and resilient operations.

# References

[1] Jaller, M., and A. Pahwa. Analytical Modeling Framework to Assess the Economic and Environmental Impacts of Residential Deliveries, and Evaluate Sustainable Last-Mile Strategies. *UC Davis: National Center for Sustainable Transportation*. 2020 http://dx.doi.org/10.7922/G21Z42PK.

[2] Tierney, K., and M. Bruneau. Conceptualizing and measuring resilience: A key to disaster loss reduction. *TR news*, No. 250, 2007.

[3] Bruneau, M., S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O'Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. Von Winterfeldt. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake spectra*, Vol. 19, No. 4, 2003, pp. 733-752.

[4] U.S. Census Bureau. *Estimated Quarterly U.S. Retail Sales (Adjusted): Total and E-commerce.* https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf.

[5] Jaller, M., and A. Pahwa. Evaluating the environmental impacts of online shopping: A behavioral and transportation approach. *Transportation Research Part D: Transport and Environment*, Vol. 80, 2020.

[6] Leatherby, L., and D. Gelles. How the Virus Transformed the Way Americans Spend Their Money. *The New York Times*. https://www.nytimes.com/interactive/2020/04/11/business/economy/coronavirus-us-economy-spending.html.

[7] World Health Organization. *WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020*. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020.

[8] Knoll, C. Panicked Shoppers Empty Shelves as Coronavirus Anxiety Rises. *The New York Times*. https://www.nytimes.com/2020/03/13/nyregion/coronavirus-panic-buying.html.

[9] Rivera-Royero, D., and M. Jaller. Impacts of Precautionary and Opportunistic Buying Behaviors on Supply Chain Resilience During the COVID-19 Pandemic. In *Transportation Research Board 101st Annual Meeting*, Washington, D.C., 2022.

[10] Office of Governor Gavin Newsom. *Governor Gavin Newsom Issues Stay at Home Order*. https://www.gov.ca.gov/2020/03/19/governor-gavin-newsom-issues-stay-at-home-order/.

[11] ---. *As California Fully Reopens, Governor Newsom Announces Plans to Lift Pandemic Executive Orders*. https://www.gov.ca.gov/2021/06/11/as-california-fully-reopens-governor-newsom-announces-plans-to-lift-pandemic-executive-orders/.

[12] Maheshwari, S., and M. Corkery. U.S. Retail Crisis Deepens as Hundreds of Thousands Lose Work. *The New York Times*. https://www.nytimes.com/2020/03/30/business/coronavirus-retail-furloughs-macys.html.

[13] Jones, K. The Pandemic Economy: What are Shoppers Buying Online During COVID-19? *Visual Capitalist*. https://www.visualcapitalist.com/shoppers-buying-online-ecommerce-covid-19/.

[14] Eger, L., L. Komárková, D. Egerová, and M. Mičík. The effect of COVID-19 on consumer shopping behaviour: Generational cohort perspective. *Journal of Retailing and Consumer Services*, Vol. 61, 2021, p. 102542.

[15] Guthrie, C., S. Fosso-Wamba, and J. B. Arnaud. Online consumer resilience during a pandemic: An exploratory study of e-commerce behavior before, during and after a COVID-19 lockdown. *Journal of Retailing and Consumer Services*, Vol. 61, 2021, p. 102570.

[16] Koch, J., B. Frommeyer, and G. Schewe. Online shopping motives during the COVID-19 pandemic—lessons from the crisis. *Sustainability*, Vol. 12, No. 24, 2020, p. 10247.

[17] Awasthi, B., and M. Mehta. Online Shopping Intentions of Generation X, Y and Z Consumers During the Covid-19 Pandemic in India. *IUP Journal of Brand Management*, Vol. 18, No. 3, 2021.

[18] Hall, C. M., P. Fieger, G. Prayag, and D. Dyason. Panic buying and consumption displacement during COVID-19: Evidence from New Zealand. *Economies*, Vol. 9, No. 2, 2021, p. 46.

[19] Adunchezor, O., and A. Akinade. Analysis of a Shift in the Business Environment and Post-Covid-19 Consumer Behaviour (A Case Study of Residents in Lagos Nigeria). 2020.

[20] Valaskova, K., P. Durana, and P. Adamko. Changes in consumers' purchase patterns as a consequence of the COVID-19 pandemic. *Mathematics*, Vol. 9, No. 15, 2021, p. 1788.

[21] Maheshwari, S., and M. Corkery. Curbside pickup is another innovation that is likely to outlast the pandemic. *The New York Times*. https://www.nytimes.com/2020/10/09/business/curbside-pickup-is-another-innovation-that-is-likely-to-outlast-the-pandemic.html?searchResultPosition=500.

[22] Creswell, J. Amazon Has a Business Proposition for You: Deliver Its Packages. *The New York Times*. https://www.nytimes.com/2018/06/28/technology/amazon-start-up-delivery-services.html.

[23] Weise, K. When Even Amazon Is Sold Out of Exploding Kittens. *The New York Times*. https://www.nytimes.com/2020/04/17/technology/amazon-coronavirus.html?searchResultPosition=89.

[24] Abadi, A., and P. Ioannou. Optimization strategies for resilient freight transport and sustainability. In *53rd IEEE Conference on Decision and Control*, IEEE, 2014. pp. 6472-6477.

[25] Serulle, N. U., K. Heaslip, B. Brady, W. C. Louisell, and J. Collura. Resiliency of transportation network of Santo Domingo, Dominican Republic: case study. *Transportation Research Record*, Vol. 2234, No. 1, 2011, pp. 22-30.

[26] Ta, C., A. V. Goodchild, and K. Pitera. Structuring a Definition of Resilience for the Freight Transportation System. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2097, No. 1, 2009, pp. 19-25.

[27] Janić, M. Modeling the resilience of an airline cargo transport network affected by a large scale disruptive event. *Transportation Research Part D: Transport and Environment*, Vol. 77, 2019, pp. 425-448.

[28] Fletcher, D. R., and D. S. Ekern. Understanding Transportation Resilience: A 2016-2018 Roadmap. In *Special Committee on Transportation Security and Emergency Management (SCOTSEM) Annual Meeting Tucson, Arizona.* http://onlinepubs.trb.org/onlinepubs/nchrp/docs/NCHRP20-59(14)C_UnderstandingTransportationResilience-Roadmap.pdf, 2016.

[29] Rivera-Royero, D., G. Galindo, M. Jaller, and J. B. Reyes. Road network performance: a review on relevant concepts. *Computers & Industrial Engineering*, 2022, p. 107927.

[30] Cantillo, V., L. F. Macea, and M. Jaller. Assessing vulnerability of transportation networks for disaster response operations. *Networks and Spatial Economics,* Vol. 19, No. 1, 2019, pp. 243-273.

[31] Hosseini, S., K. Barker, and J. E. Ramirez-Marquez. A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, Vol. 145, 2016, pp. 47-61.

[32] Faturechi, R., and E. Miller-Hooks. Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review. *Journal of infrastructure systems,* Vol. 21, No. 1, 2015, p. 04014025.

[33] Biringer, B., E. Vugrin, and D. Warren. *Critical infrastructure system security and resiliency*. CRC press, 2013.

[34] Zhou, Y., J. Wang, and H. Yang. Resilience of transportation systems: concepts and comprehensive review. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 20, No. 12, 2019, pp. 4262-4276.

[35] Adams, T. M., K. R. Bekkem, and E. J. Toledo-Durán. Freight Resilience Measures. *Journal of Transportation Engineering,* Vol. 138, No. 11, 2012, pp. 1403-1409.

[36] Sahebjamnia, N., S. A. Torabi, and S. A. Mansouri. Integrated business continuity and disaster recovery planning: Towards organizational resilience. *European Journal of Operational Research,* Vol. 242, No. 1, 2015, pp. 261-273.

[37] Zobel, C. W. Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems,* Vol. 50, No. 2, 2011, pp. 394-403.

[38] Zobel, C. W., and L. Khansa. Characterizing multi-event disaster resilience. *Computers & operations research,* Vol. 42, 2014, pp. 83-94.

[39] Oyola, J., H. Arntzen, and D. L. Woodruff. The stochastic vehicle routing problem, a literature review, part I: models. *EURO Journal on Transportation and Logistics,* Vol. 7, No. 3, 2018, pp. 193-221.

[40] ---. The stochastic vehicle routing problem, a literature review, part II: solution methods. *EURO Journal on Transportation and Logistics*, Vol. 6, No. 4, 2017, pp. 349-388.

[41] Nair, R., H. Avetisyan, and E. Miller-Hooks. Resilience framework for ports and other intermodal components. *Transportation Research Record,* Vol. 2166, No. 1, 2010, pp. 54-65.

[42] Chen, L., and E. Miller-Hooks. Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport. *Transportation Science,* Vol. 46, No. 1, 2012, pp. 109-123.

[43] Stamos, I., E. Mitsakis, J. M. Salanova, and G. Aifadopoulou. Impact assessment of extreme weather events on transport networks: A data-driven approach. *Transportation Research Part D: Transport and Environment*, Vol. 34, 2015, pp. 168-178.

[44] Zhu, Y., K. Ozbay, K. Xie, and H. Yang. Using big data to study resilience of taxi and subway trips for Hurricanes Sandy and Irene. *Transportation Research Record,* Vol. 2599, No. 1, 2016, pp. 70-80.

[45] Vugrin, E. D., D. E. Warren, and M. A. Ehlen. A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane. *Process Safety Progress,* Vol. 30, No. 3, 2011, pp. 280-290.

[46] Hallegatte, S., and J. Rentschler. *The Last Mile: Delivery Mechanisms for Post-Disaster Finance*. World Bank, 2018.

[47] Hobbs, J. E. Food supply chains during the COVID-19 pandemic. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie,* Vol. 68, No. 2, 2020, pp. 171-176.

[48] ---. Food supply chain resilience and the COVID-19 pandemic: What have we learned? *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie,* Vol. 69, No. 2, 2021, pp. 189-196.

[49] Ali, M. H., N. Suleiman, N. Khalid, K. H. Tan, M.-L. Tseng, and M. Kumar. Supply chain resilience reactive strategies for food SMEs in coping to COVID-19 crisis. *Trends in Food Science & Technology*, 2021.

[50] Herold, D. M., K. Nowicka, A. Pluta-Zaremba, and S. Kummer. COVID-19 and the pursuit of supply chain resilience: reactions and "lessons learned" from logistics service providers (LSPs). *Supply Chain Management: An International Journal*, 2021.

[51] Burgos, D., and D. Ivanov. Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 152, 2021, p. 102412.

[52] Moosavi, J., and S. Hosseini. Simulation-based assessment of supply chain resilience with consideration of recovery strategies in the COVID-19 pandemic context. *Computers & Industrial Engineering,* Vol. 160, 2021, p. 107593.

[53] Singh, S., R. Kumar, R. Panchal, and M. K. Tiwari. Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research,* Vol. 59, No. 7, 2021, pp. 1993-2008.

[54] Srinivas, S. S., and R. R. Marathe. Moving towards "mobile warehouse": Last-mile logistics during COVID-19 and beyond. *Transportation Research Interdisciplinary Perspectives,* Vol. 10, 2021, p. 100339.

[55] Amazon.com, Inc. *Amazon Flex*. https://flex.amazon.com/.

[56] CoStar. https://www.costar.com.

[57] Shen, C. Y. Logistic growth modelling of COVID-19 proliferation in China and its international implications. *International Journal of Infectious Diseases,* Vol. 96, 2020, pp. 582-589.

[58] Triambak, S., D. Mahapatra, N. Mallick, and R. Sahoo. A new logistic growth model applied to COVID-19 fatality data. *Epidemics,* Vol. 37, 2021, p. 100515.

[59] Liu, L., H. J. Miller, and J. Scheff. The impacts of COVID-19 pandemic on public transit demand in the United States. *PLOS One,* Vol. 15, No. 11, 2020, p. e0242476. https://doi.org/10.1371/journal.pone.0242476

[60] UPS. UPS Pulse of the Onlnine Shopper Study - Global Study. In, 2018.

[61] Caltrans. California Life-Cycle Benefit/Cost Analysis Model (Cal-B/C). In, 2017.

[62] Marten, A. L., and S. C. Newbold. Estimating the social cost of non-CO2 GHG emissions: Methane and nitrous oxide. *Energy Policy*, Vol. 51, 2012, pp. 957-972.

[63] Jaller, M., L. Pineda, and H. Ambrose. Evaluating the Use of Zero-Emission Vehicles in Last Mile Deliveries. In *UC Davis Institute of Transport Studies*, University of California, Davis, Davis, CA, 2018.

[64] Caltrans. *Vehicle Operation Cost Parameters*. https://dot.ca.gov/programs/transportation-planning/economics-data-management/transportation-economics/vehicle-operation-cost-parameters.

[65] AAA. *State Gas Price Averages*. https://gasprices.aaa.com/state-gas-price-averages/.

[66] California Air Resource Board. *EMFAC2017 Web Database*. https://www.arb.ca.gov/emfac/2017/.

[67] Renne, J., B. Wolshon, P. Murray-Tuite, and A. Pande. Emergence of resilience as a framework for state Departments of Transportation (DOTs) in the United States. *Transportation Research Part D: Transport and Environment*, Vol. 82, 2020, p. 102178.

[68] Figliozzi, M., and A. Unnikrishnan. Home-deliveries before-during COVID-19 lockdown: Accessibility, environmental justice, equity, and policy implications. *Transportation Research Part D: Transport and Environment*, Vol. 93, 2021, p. 102760.

[69] Esmalian, A., F. Yuan, A. A. Rajput, H. Farahmand, S. Dong, Q. Li, X. Gao, C. Fan, C.-C. Lee, and C.-W. Hsu. Operationalizing resilience practices in transportation infrastructure planning and project development. *Transportation Research Part D: Transport and Environment*, Vol. 104, 2022, p. 103214.

[70] Kurth, M., W. Kozlowski, A. Ganin, A. Mersky, B. Leung, J. Dykes, M. Kitsak, and I. Linkov. Lack of resilience in transportation networks: Economic implications. *Transportation Research Part D: Transport and Environment*, Vol. 86, 2020, p. 102419.