Impacts of Precautionary and Opportunistic Buying Behaviors and Supply Issues on Supply Chain Resilience During the COVID-19 Pandemic

Daniel Rivera-Royero[1] (iD), Miguel Jaller[2] (iD), and Alan Jenn[3] (iD)

Abstract

This paper proposes a text analytics approach using dictionary-based clustering, word counting data, and discrete regression modeling to study the relationship between demand behaviors and supply issues affecting supply chain resilience during the first stages of the COVID-19 pandemic. The work used news and media articles gathered from the LexisNexis database covering 5 months between February and July 2020. The data analyses describe the general patterns in the news texts by using text mining techniques, and the methodology describes the relationship between consumer behavior, supply chain issues, and the reduced level of service shown during the study period. Demand behaviors include precautionary and opportunistic buying, which affected many countries and could be the result of a lack of perceived control and other factors; for example, near-empty shelves of certain products could have prompted consumers to increasingly look for comparable products, driving up demand. Additionally, the method explored the potential effect of strategies to mitigate impacts on the resilience of supply chains. The results confirmed that buying behaviors and a reduction in the capacity of the supply chain led to a lower level of service being perceived by consumers, however, resilience strategies were found to mitigate the impact of such capacity reductions. Empirical analyses showed that the proposed approach, using data extracted from the news, could identify and represent impacts consistent with expectations from the supply chain field under disruptions, and quantify the magnitude of the impacts as the pandemic evolved, providing more information for decision making.

Keywords

freight, resilience, sustainability, supply chain, logistics

Introduction

Precautionary and opportunistic buying of goods can be a common phenomenon during natural or manufactured disasters (*1*), and although it has been studied in the past, its causes may be different under a pandemic setting, for example, COVID-19 (*2*). White (*3*) and Barnes et al. (*4*) consider that precautionary and opportunistic buying behaviors may evolve during a pandemic, and that high demand shocks will usually lead to shortages of essential products (e.g., food, medical supplies, personal hygiene, and protective equipment) and services (*5*). In other words, different forms (and manifestations) of these behaviors occur during disruptive events and can create havoc in the supply of essential products and services. For instance, at the beginning of the COVID-19 pandemic, governments around the world implemented orders to manage the movement of people and the closure of nonessential businesses, this was followed by precautionary and opportunistic buying behavior or "panic buying" (PB) as it was termed by the media. This situation caught retailers and supply chains (SCs) by surprise,

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[1]Institute of Transportation Studies, University of California, Davis, CA
[2]Sustainable Freight Research Program, Institute of Transportation Studies, Department of Civil and Environmental Engineering, University of California, Davis, CA
[3]Plug-in Hybrid and Electric Vehicle (PH&EV), Institute of Transportation Studies, University of California, Davis, CA

Corresponding Author:
Miguel Jaller, mjaller@ucdavis.edu

and with the absence of a supply buffer, also created more obstacles for response agencies trying to access essential items—similarly for the public, including vulnerable populations (e.g., seniors, those on low income, individuals with disabilities, and/or illnesses). One noticeable consequence was the rapid spread of images of empty shelves across the media and an increase in the prices of products, and in the time required to deliver them. With physical stores and businesses temporarily closed, demand shifted to online channels (6). However, the distribution capacity of e-retailers was also affected because they faced an unprecedented surge in demand, and many had personnel across their different facilities who were also directly affected by the pandemic. Nevertheless, these companies tried to continue to provide fast, cheap, and reliable deliveries, although the level of service (LOS) was lower than before the pandemic (7).

Overall, characterizing the impacts of the disruptions caused by COVID-19 and the behaviors that ensued in the SCs of critical goods became important, as well as understanding the potential opportunities to mitigate such effects. Thus, it was identified as critical to identify mitigation strategies that could help to guarantee the fluidity of goods and to maximize accessibility and minimize human suffering (8, 9). Furthermore, understanding the potential impact of buying behaviors on demand and supply was highlighted as important, but building resilient SCs was crucial (4).

Consequently, the main objective of this research was to understand and quantify the relationship between demand behaviors and SC limitations and opportunities concerning the reduced LOS perceived during the first stages of the COVID-19 pandemic. To do so, the authors proposed and implemented a text analytics approach using secondary data. During the pandemic, social networks, social media, and news outlets played a significant role in the communication and dissemination of information, and portrayed the conditions in relation to health, the economy, and public opinion around the world. Therefore, this study concentrated on the analyses of news and other media articles collected from the LexisNexis database, published between February 1 and July 30, 2020, related to SC disruptions. For instance, the data include news, from multiple sources and geographic areas, from the time the disease started to propagate in late February, when most countries imposed quarantine and stay-at-home orders around March, and when some of these strategies were relaxed in May and June of that year. News and mass media coverage may concentrate on specific issues and portray those that are perceived to be more attractive to the mass market (i.e., reader/viewer), while overlooking others, raising concerns about the validity and accuracy of the information provided (10, 11). However, there was a continuous influx of media coverage from various sources that was able to capture, at least partially, the key issues faced on the ground, and in many cases included direct observations from or interviews with different stakeholders.

SC disruption and resilience are topics that have received significant attention from researchers (12, 13), practitioners, and planners, therefore there is a body of knowledge about SC disruptions; a secondary objective of the research, therefore, was to evaluate whether the data extracted from the media could help validate hypotheses consistent with expectations from the SC field. Consequently, this paper provides a descriptive analysis of the data extracted from the news by using several text mining techniques: sentiment- and topic analysis, and word combination graphs. Based on the analyses, the authors developed topic categories and word and phrase dictionaries to translate news into data to implement quantitative analysis methods. Specifically, the authors constructed an incidence and flow graph showing the hypothesized relationships between demand behaviors, SC capacity and flow issues, and resilience strategies on the resulting LOS of the SC distribution. Although the data extracted from the news and their granularity may only evidence the existence of causal relationships between the factors, the authors introduced several hypotheses based on the expected disruption impacts (12, 13), with the nodes and arcs in the incidence graph representing the relationship and impact direction between the factors. The authors evaluated and quantified these relationships through discrete regression modeling, and the results showed that the data and models confirmed the hypotheses.

Overall, the contributions of this research are (1) development of a data analytics approach that can process information from news and media to identify relationships between factors (e.g., precautionary and opportunistic buying, capacity reductions) affecting SC resilience; (2) quantification of the relative importance of the factors, their direction of impact, and their effect as the disruption evolves; (3) evaluation of the effect of SC resilience strategies to mitigate any impacts; and (4) translation of the continuous flows of news into dynamic data representing the evolution of behaviors and issues throughout the disruption to support decision making.

Literature Review

Precautionary and opportunistic buying refers to the shopping behaviors resulting from the perception and anticipation of needs after a disruptive event or supply uncertainties. In extreme cases, these behaviors can result in stockpiling, hoarding, and shop-raiding (14–16). During the COVID-19 pandemic, these buying behaviors may have led to stock-outs and disruptions in SCs. Such buying behavior is an example of the tragedy of the

commons, where entities try to increase their benefits without caring about the capacity of the system, and the result of this selfish behavior is the ruin of the system and the ruin of all the entities involved (*17*). Precautionary and opportunistic buying has been analyzed in multiple disciplines from an academic perspective (e.g., psychology [*18*]) and in relation to industry (e.g., engineering, marketing research) (*19*).

From an engineering perspective, Zheng et al. investigated the impact of consumers' social learning on their decisions to buy under supply disruption risk (*13*). They also analyzed how retailers should manage this by using inventory ordering optimization. Tsao et al. examined how optimal ordering quantities are affected by PB when retailers sell substitute products (*20*). Yoon et al. additionally analyzed the strategies used by retailers when sourcing, and focused on the scenario of PB under the risk of SC disruption (*21*). Remko considered PB to be a demand risk, and provides a set of resilience strategies depending on the risk involved in the SC, based on the literature and on the views of participating SC executives (*22*). Research by Hobbs provides an overview of the consequences of the COVID-19 pandemic in relation to demand and supply shocks, as well as the expected long-run changes that require the food SC to be resilient against future pandemic situations (*23*).

Precautionary and opportunistic buying, or PB, has been widely studied from a psychological perspective (*4, 18, 24–29*). For instance, Yuen et al. reviewed, identified, and synthesized their psychological causes, for example, individuals' perception of the threat of the health crisis and the scarcity of products; fear of the unknown; coping behaviors; and social psychological factors (*18*). Arafat et al. similarly considered perception of scarcity to be linked to PB behavior, and that hoarding behavior increases when scarcity increases (*24*). Taylor discusses how PB arises when governments ask for self-isolation as an intervention to contain a virus during a pandemic and PB usually lasts 7 to 10 days (*28*). Precautionary and opportunistic buying typically starts from a position of fearf, and this consumer fear snowballs via social media, prompted by images and videos of empty shelves across stores. Ultimately, this fear becomes a reality when short-term scarcity occurs (*28*). Some authors concur that the collection of things is a mechanism to fight the feeling of insecurity (*30*). In other words, the act of purchasing is a remedy to reduce the fear and anxiety of losing control.

A common way of analyzing these behaviors during the COVID-19 pandemic in the field of psychology was by analyzing media reports, as in the research undertaken by Barnes et al. (*4*) and Arafat et al. (*27, 29*). For instance, Arafat et al. consider that the media plays a key role in the population perceptions of precautionary

and opportunistic buying, and it could equally play an important role in the prevention of it (*27*). Arafat et al. analyzed 214 news reports from around the world and highlighted that the term "panic buying" was typically used in media reports from developed nations (*29*). Arafat et al. performed an analysis of news in Bangladesh and limited their search to 24 reports (*31*). In those reports, the authors identified the themes, the goods involved, the events that occurred, and the prevention strategies used. The most common goods were found to be unperishable goods, sanitary items, and personal protective equipment; the most common event was an increase in demand; and the most common preventive strategies were rationing, raising awareness, and government management of the prices. The most structured text analytic paper found on this topic was by Barnes et al. (*4*). Using Twitter data, this paper provides an innovative methodology that analyzes consumer behavior during the COVID-19 pandemic in Italy. The methodology considers compensatory control theory, text analytics, and data modeling, and provides evidence that a lack of perceived control, fear, and anxiety affect customer buying behaviors. Barnes et al. also identified research gaps, for example, to analyze the relationship between consumer buying behavior and SC deficiencies and opportunities around the reduced LOS perceived by consumers (*4*). Text analytics is a methodology that is widely used in natural disaster analysis (*32*), for instance, Huizinga et al. analyzed the relationship between natural disasters and insurance by using around 19,000 tweets on more than 11,000 natural disasters (*33*). Goh and Sun studied citizens' opinions and discovered social insights into natural disasters, which are vital for policy makers and for business decisions (*34*).

This study builds on the methods used by Barnes et al. (*4*) and expands the analyses by considering consumer perceptions of LOS and the SC effects in the set of relationships and hypotheses. As stated, this study attempts to show whether the news can provide insights into SC resilience and quantify the effects of contributing factors and mitigating strategies. This study has additionally tried to fill the gap identified by Billore and Anisimova of insufficient research on precautionary and opportunistic buying in the contexts of retailer behavior and SC management (*19*).

Data Description

The authors used LexisNexis as the data source for the analyses—a database that provides full-text access to historical news archives, local news, global news, company and executive data, and legal documents (*35*). Data collection used the following query: "(Supply Chain OR Supply-Chain) AND (COVID OR Coronavirus) AND
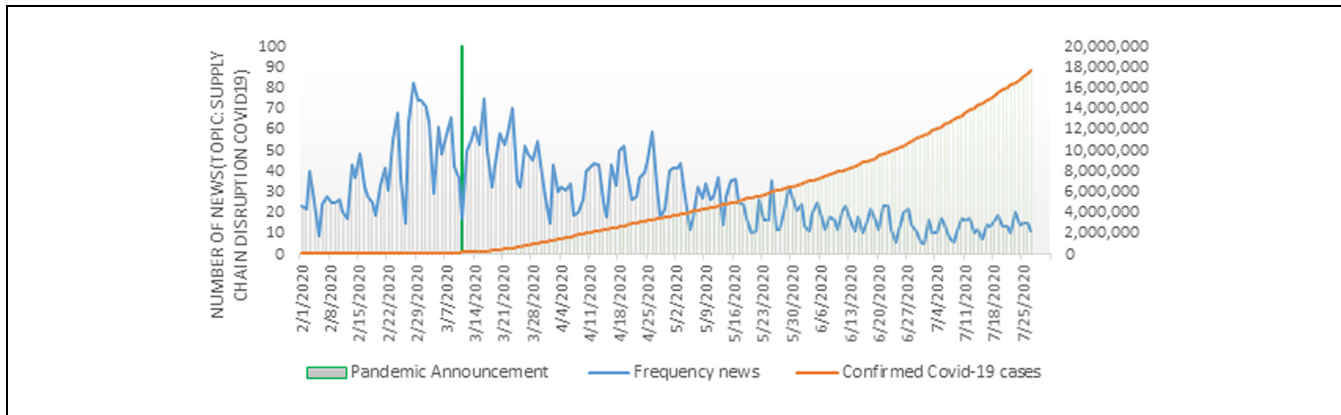
Figure 1. Number of articles per month (*37*) and confirmed COVID-19 cases.

(Disruption OR Resilience) AND (Retailer OR Warehouse OR Transportation OR Factory)." The search was limited to news articles in English from February 2000 to July 2020, and identified around 7,362 news items, 69 of which were initially discarded because they did not have a date. After implementing text analyses on the remaining articles, the authors identified and discarded about 1,540 news items because of very high similarity between the texts, resulting in 5,671 pieces of news. Finally, a similarity analysis was carried out, based on a relative modification of the generalized Levenshtein- and the relative distance on all the articles by grouping them by day (*36*), resulting in 5,264 news items. Figure 1 shows the daily frequency of the news considered in this study and the worldwide confirmed deaths from COVID-19. The number of news items peaked during March 2020, and then slowly declined during the next 4 months.

Figure 2 shows a worldwide map of COVID-19 cases per capita (thousands). Note that in February, China led the COVID-19 cases around the world, ranging from 0.9 to 1 case per 1,000 habitants (Figure 2). Then, between March and July, India and the United States had the highest positive rates of COVID-19. Brazil and Russia also had relatively high COVID-19 positive cases in comparison with the rest of the world. Some European countries like Spain, France, Portugal, and Italy also had high COVID-19 cases at the beginning of March, whereas COVID-19 cases in Latin American countries such as Brazil, Peru, and Colombia peaked around April. It is worth noting that the United States, China, Australia, Canada, and Mexico had the highest frequency of news items in the sample. Figure 3 shows a sample of how the frequency of news items evolved in the United States between February and July. Note that there are differences in the number of unique news depending on time and geographic location.

Figure 4 shows a wordcloud of the 500 most frequently used words in our data set. It highlights coronavirus, time, supply, government, people, China, and COVID, among other terms. As stated, news and media provided a continuous flow of news from diverse sources (from different geographies) that provided a good representation of the most important occurrences during the pandemic. Moreover, considering that during disruptions and disasters, news, while imperfect, serves as a general source of widespread information, the authors decided to explore its use, despite the potential shortcomings. During other events, studies using information from social media, which could be even more problematic, have shown benefits (*4, 31, 38*). In summary, the study explored news media because they represent an opportunity to use secondary data that is updated every day (although there is duplication of news that we identified and corrected for) and to provide information about the most recent events, which is the purpose of news, to inform. Recall, one of the key goals of the study was to evaluate the feasibility of using this secondary information and translate it into actionable data for decision making.

Methodology

The study developed an approach that could be used to understand the relationships between events and observed effects and to subsequently predict behaviors pertaining to a particular issue, such as the evolution of topics across time and space, which could provide valuable information to prioritize actions and allocate scare resources. The approach had two main components. First, data analytic techniques were implemented to process the information contained in the news articles, and second, to determine the relationship between distinct factors and the resilience of SCs. Therefore, the authors implemented a
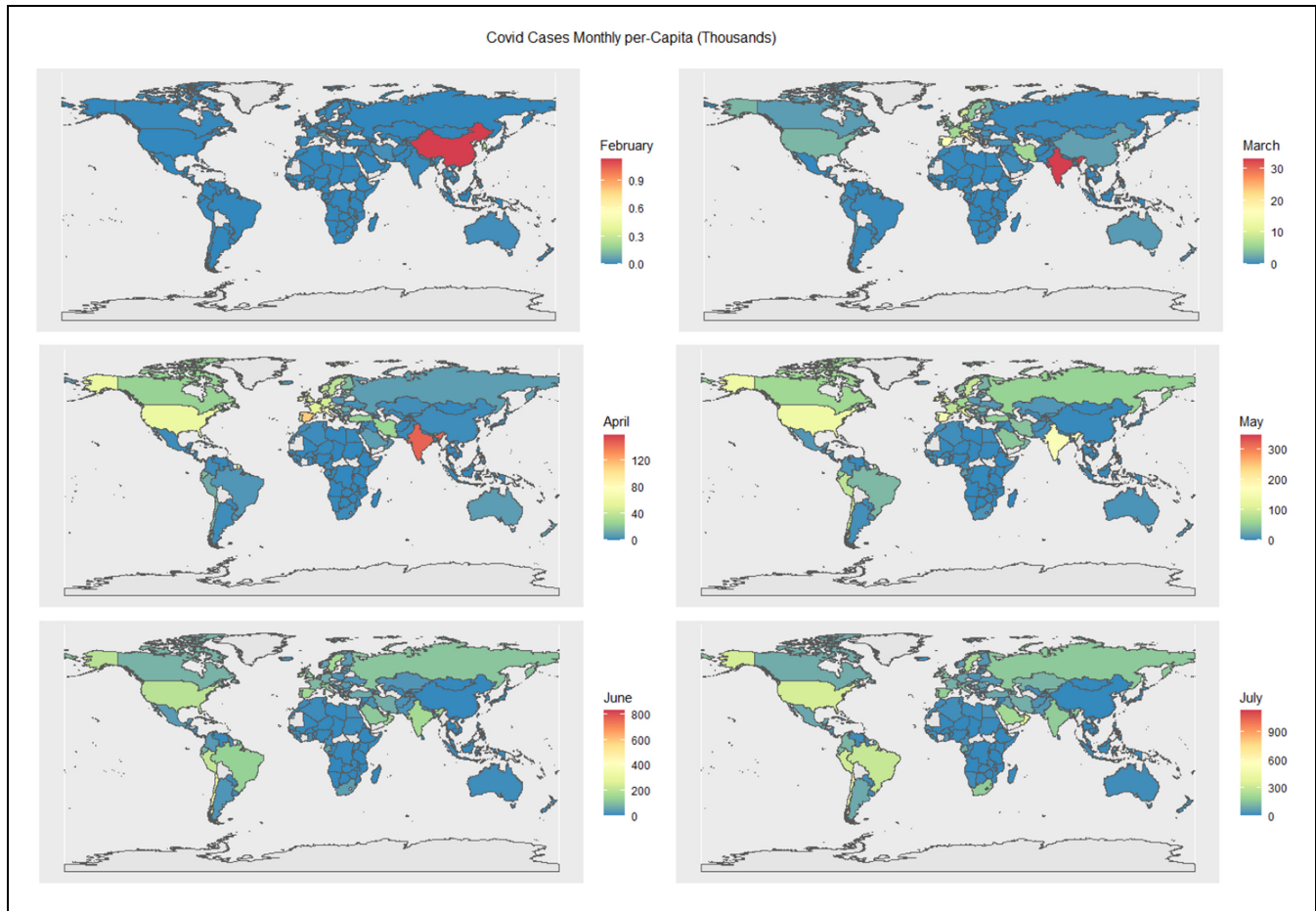
Figure 2. Monthly COVID-19 positive cases per capita (thousands) worldwide (*37*).

comprehensive approach that involved relationship analysis, dictionary-based clusters, and discrete regression analysis.

Data and Text Analysis

Various analyses were performed in the exploration of the raw data, one of which was sentiment analysis: the authors analyzed the sentiment of the news by considering the text in the news as a combination of its individual words. Therefore, the data set was the sum of the sentiment content of the most frequent words, having discarded stop words. There are several sentiment lexicons (i.e., a list of English positive and negative opinion or sentiment words), for example, "affin," "nrc," and "bing," lexicons. This paper shows an example in Figure 5 using the bing lexicon because of its simplicity. This bing lexicon (comprising around 6,800 words) was compiled by Hu and Liu (*39*), and categorizes positive and negative words in a binary fashion (*40*). Figure 5 shows that the most frequently appearing words had a mainly negative sentiment, as expected given the pandemic (*41*).

Another method used to explore the raw data was topic modeling: an unsupervised classification method for documents, clustering on numeric data (*40*). Topic modeling finds natural groups of items by following a latent Dirichlet allocation (LDA) method. LDA is a generative probabilistic model for text corpora (*42*), which allows the modeling of a set of topic probabilities for each corpora by using a three-level hierarchical Bayesian model (*42*). LDA topic analysis requires input parameters to increase their performance, for example, the number of topics (k) and a prior Dirichlet topic distribution in the function. However, finding the best number of topics is challenging (*43*), especially if there is no prior knowledge about the data. The LDA topic model has a problem in that it does not give the optimal number of topics for the text itself, the exact number of topics being determined by the model user in other ways (*44*). For instance, by using perplexity, coherence, r-squared (R^2), log-likelihood, and prevalence. If prevalence is the incidence of the topic in all documents across the corpus, then coherence is a measurement that approximates the semantic coherence or human understandability of a
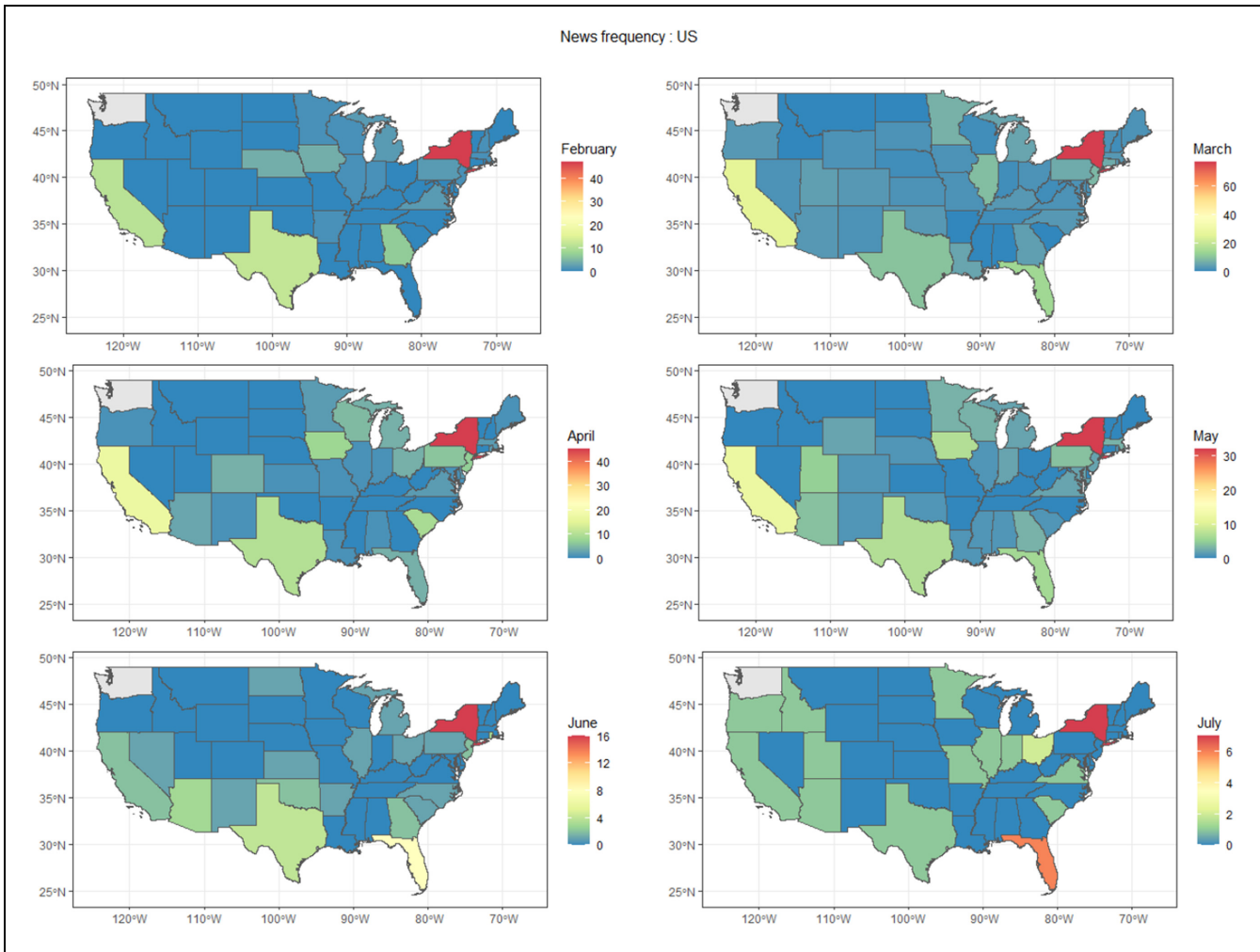
Figure 3. Sample news frequency by month in the United States.

topic (*45*), and R^2 represents the proportion of variability in the data that the topic model explains. Perplexity evaluates the models on held-out data (i.e., labeled data used for training and validation) and is equivalent to the geometric mean per-word likelihood (*46*). When evaluating the performance of LDAs by using perplexity, the lower the perplexity value, the better the performance (*47*). However, the perplexity metric has some drawbacks, for instance, when k increases, perplexity diminishes. This makes it difficult to identify the optimal number of topics. Coherence is a method of identifying the optimal number of topics, coherence and R^2 are better when their values increase. When considering log-likelihood, the k with the maximum likelihood is the best. Figure 6 shows two sets of words that determine the topics identified in the news for representation purposes and simplicity; because LDA models with two topics are more consistent with human intuition than when the number of

topics increases, the authors used two topics (*44*). A detailed analysis of topic selection number can be found in Supplemental Material.

Analyzing the words in the two identified topics, the authors labeled the first topic as "COVID-19 pandemic on health, government, and countries" and the second as "COVID-19 pandemic on supply economy, market, and companies." In general, the former refers to the social- and system effects, and latter to the private impacts. Both topics have common terms, for example, coronavirus, supply, China, as such terms are key to the selected news. Figure 7 shows a bigram (network) that indicates the words that tend to follow certain other words more frequently (frequency ⩾ 150). The bigram allows identification of how often word X is followed by word Y, making it possible to build a model of the relationships between them, for instance, "private → sector," "manufacturing → sector." Note in Figure 7 the existence of six

Figure 4. The 500 most frequent words: wordcloud.

Figure 5. Sentiment analysis of the most frequent words appearing in the news.

clusters of words, which the authors labeled "supply chain," "COVID," "health," "economy," "countries/cities," and "measures." It also evidences a relationship between SC terms and food security, and with the global economy, as well as with market, disruption, and crisis. This latter word, crisis, has a significant role because it connects most clusters: "supply chain," "health," "economy," "measurement," and "Covid-19." Note that

"health" has a direct relationship with safety "measures." In other words, the COVID-19 pandemic developed as a "crisis" not only in relation to health but also in global and local economies, as well as in the SCs that supported economic systems.

The authors also analyzed the evolution of topics and terms in the news; for example, Figure 8 shows that the frequency of term use varies over time, indicating the relative importance of a term over an entire text, and its individual frequency pattern. As shown in Figure 8, whereas the frequency of some words increased over time, their density may have been concentrated within specific periods. For instance, hoarding and stockpiling seemed to be prevalent within the total word count, however, when the terms were treated independently through time, their prevalence seemed to vary slightly. Overall, news items and word counts would be expected to be affected by time, space, and especially the occurrence of events (e.g., COVID-19 cases, and government announcements). The data analysis approach can therefore be used to monitor conditions and feed on the influx of news as disruptions evolve, to identify patterns and prioritize actions. In addition to analyzing the impact of precautionary and opportunistic buying behaviors, one of the main intentions of this study was to identify resilience strategies reported in the news that could be implemented in future pandemic situations, to avoid or mitigate similar issues like the ones faced during the COVID-19 pandemic. Note that the preliminary text analysis presented here does not provide insights into specific resilience strategies that might be used in SCs. Moreover, identifying the key factors affecting SCs and the topics discussed in the news is still necessary. These factors involve buying behaviors, SC issues, and opportunities. The authors considered a dictionary-based clustering approach by using words with similar meanings/contexts consistent with descriptions of the relationships.

Relationship Analysis

The terms precautionary and opportunistic buying or panic buying have been widely analyzed in the literature from a psychological perspective during the early stages of the pandemic (*4*); however, their relationship with SC resilience has not been widely explored using text analytics. The news articles were expected to depict the demand spikes of essential products (shocks) and the demand reduction of nonessential products as being affected by the pandemic. On the supply side, identification of issues related to shortages of essential products was anticipated, such as food (meat), medical products, and raw materials for specific industries (e.g., cellphones), and the reduction of SC capacity because of labor, product, and equipment shortages. The reduced productivity of a SC was perceived by delayed shipments, payments, and production,
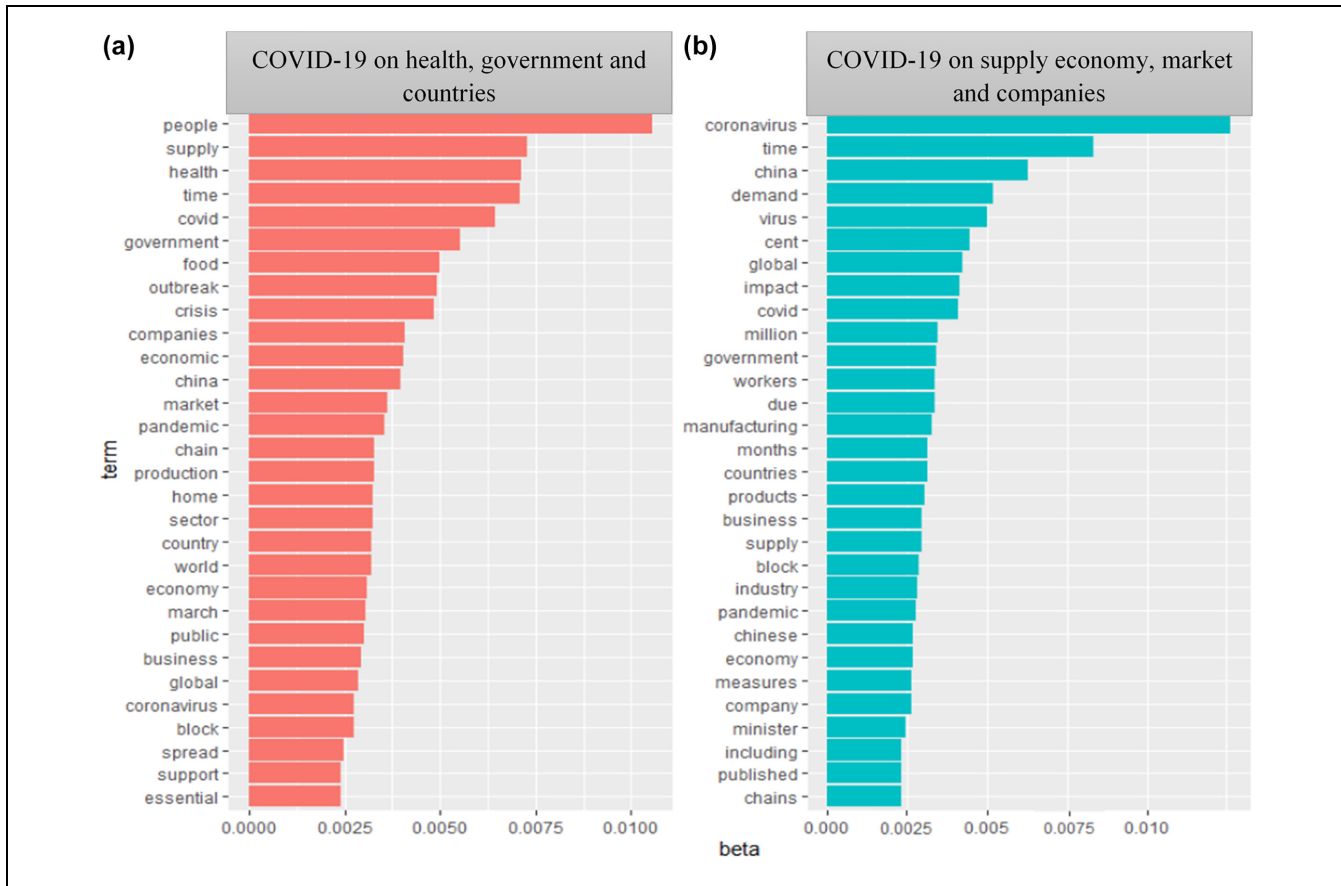
Figure 6. Per-topic-per-word probability clusters: (*a*) COVID-19 pandemic on health, government, and countries; (*b*) COVID-19 pandemic on supply economy, market, and companies.

as well as disruption to and challenges with cash flow. Reasons that triggered SC collapse and the ensuing ripple effect included the closure of factories, businesses, stores, facilities, restaurants, and borders because of the virus. The authors also considered resilience strategies, such as diversifying the SC or supplier network, increasing domestic production and truck loading, and sharing information, equipment, and resources. Boosting food production, increasing the use of information technologies, growing online sales and home delivery, and reducing delivery times were among the strategies mentioned in Chowdhury et al. (*12*). To mitigate the impacts of COVID-19 on labor, recommendations identified included the use of personal protective equipment and enhancing the technologies used, for example, by investing in automated manufacturing and production systems, as well as in warehouses and transportation. The approach developed here builds on the methods used by Barnes et al. (*4*) and expands to consider additional factors related to SC issues, and to resilience strategies to evaluate the impact on perceived LOS. Therefore, the

authors developed an incidence and flow graph, in which arcs and nodes represent the relationships and impact direction between the factors. Figure 9 shows the relationship graph that endeavors to emulate the connection between consumer buying behavior, SC limitations/ opportunities, and the reduced LOS perceived by consumers. Specifically, the graph considers 19 nodes and 18 arcs and maps out the set of developed hypotheses to be evaluated. Each node comprises a dictionary-based cluster that is populated with words or phrases that have similar contexts or meanings and represents a condition that the demand (consumers) and supply (SC) channels might face during the COVID-19 pandemic. The arcs represent the expected relationship between the nodes, in other words, the authors' hypotheses. Note that the consumer subgraph was partially derived from research by Barnes et al. (*4*), however, this study expanded the consumer behavior analyses by adding a set of relationships and hypotheses for the downstream SC.

In Figure 9 the consumer group contains four nodes: anxiety and fear, lack of perceived control, purchase,
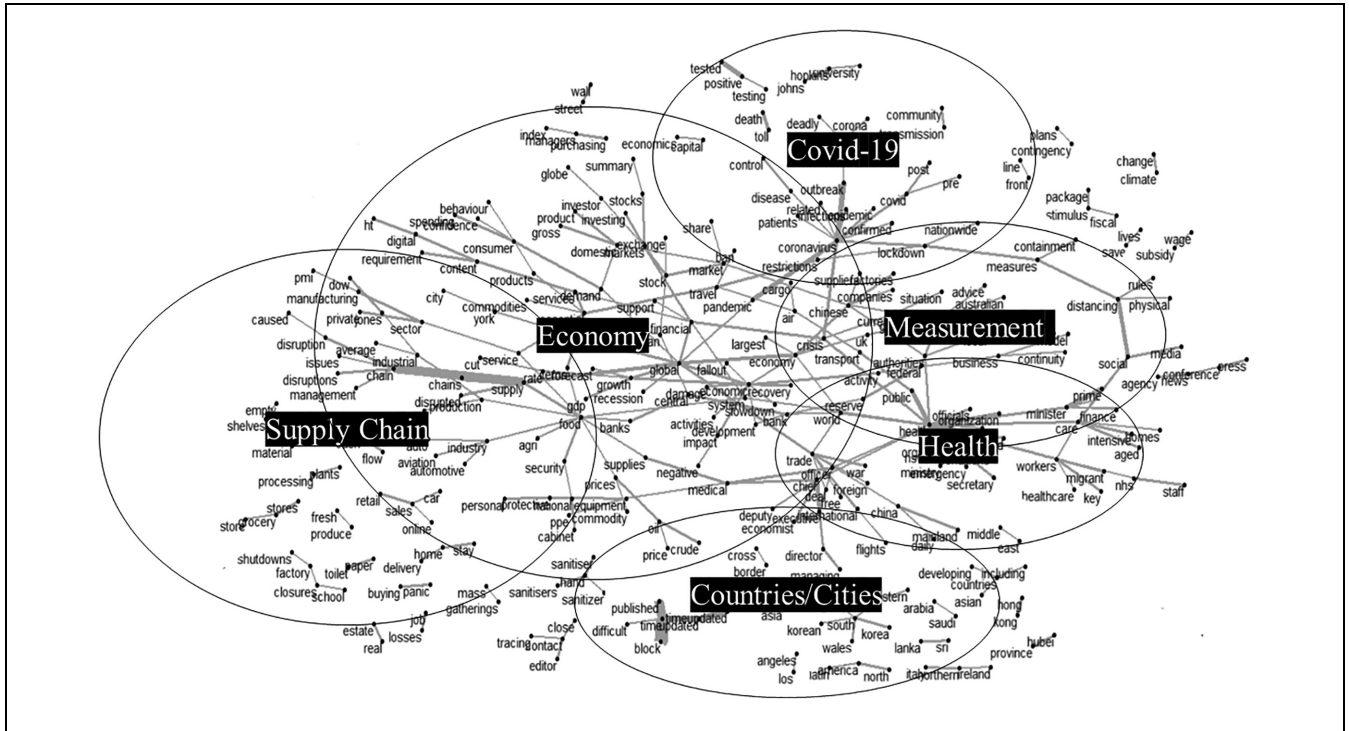
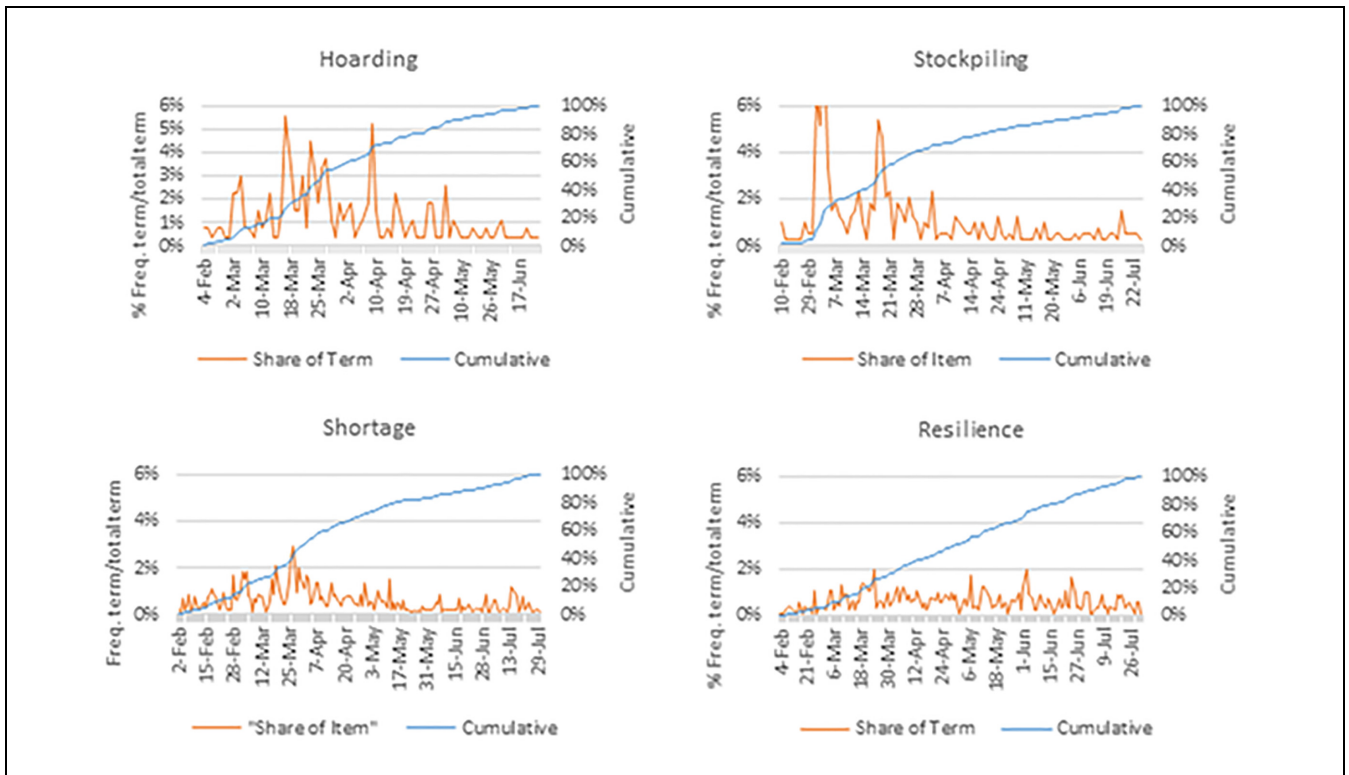**Figure 7.** Most frequently used words connection on news.

Figure 8. Example of term categories over time (blue indicates count over total count, while orange is the share within the specific term total count).
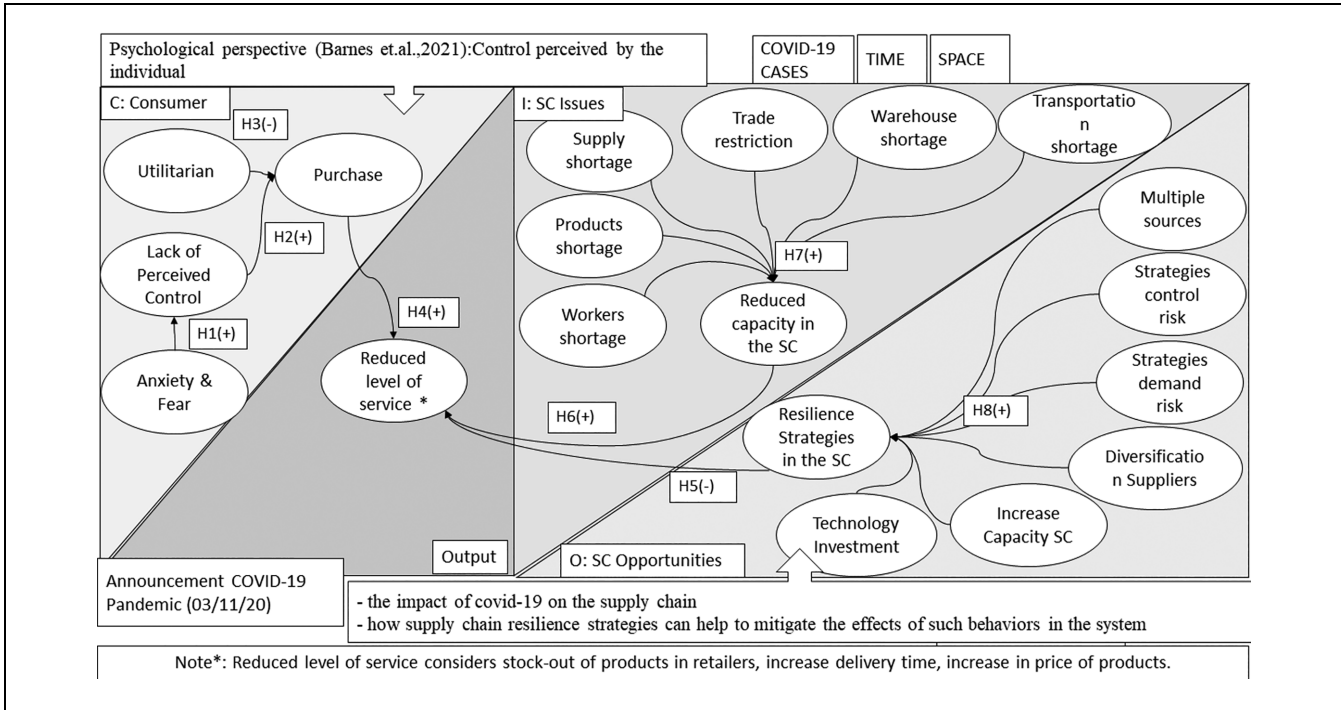
Figure 9. Research relationship graph: hypotheses and arcs.

and utilitarian goods (*4*). Each of them is a cluster of words/phrases with similar meanings, for example, the "purchase" cluster includes words like buy, shop, purchase, and bargain. There are three arcs, or hypotheses, described as follows. Hypothesis 1 or H_1 (+) connects "anxiety and fear" with "lack of perceived control": the positive symbol means that a positive relationship between both variables is expected. In other words, if a person (consumer) feels greater levels of anxiety and fear, they are more likely to experience a lack of perceived control. H_2 (+) considers that consumer "lack of perceived control" is related to "purchase": if the consumer feels that they are losing control during the pandemic they will buy more products. However, H_3 (−) considers that "utilitarian goods" will moderate the relationship between "lack of perceived control" and "purchase" because utilitarian goods have a psychological effect that will act as a defense mechanism against the uncertainties perceived during the pandemic. For instance, the buying behavior of toilet rolls and dried pasta that was witnessed early on in the pandemic was a subconscious response—preparation for a larger disaster (*4*). Note that the buying of products and goods (utilitarian goods) is also used to solve everyday problems, with the objective of influencing an individual's environment (*48*). By buying such products, people gain feelings of control (*4*).

The central node in Figure 9 is "reduced LOS" because this node represents the outcome or problem of interest, that is, the consequence of precautionary and opportunistic buying (i.e., PB) on the consumer market. Note that "reduced LOS" has two sources: consumer demand and SC disruption. An increase in demand combined with a decrease in the SC capacity is a recipe for consumer perceptions of "reduced LOS." These relationships are not unique to COVID; for any system, an increase in demand coupled with reduced capacity will translate into a deterioration of LOS. Therefore, one of the objectives in the current study was to check whether the data led to consistent results, and the other was to quantify the impacts. H_4 (+) in Figure 9 shows a positive relationship between "purchase" and "reduced LOS." This suggests that the more people bought as a result of opportunistic and precautionary buying/PB, the greater the chance of "reduced LOS." In the SC, there were two sets of nodes—those related to issues and those that involve opportunities. The "reduced capacity in the SC" node fell within the issues set and considered shortages of workers, products, supply, transportation, warehouse, and trade restrictions. The H_7 (+) arcs indicated that the shortages and restrictions were positively related to the "reduced capacity in the SC." H_6 (+) showed that the increase in the reduction of capacity in the SC increased reduced LOS, however, H_5 (−)

considered that resilience strategies in the SC might be used to mitigate the effects of the capacity reduction in the SC on reduced LOS. The H8 (+) arcs indicated that commonly used resilience strategies, such as diversifying the SC, technology, capacity increase, demand, and control strategies and multiple sources were positively related to resilience strategies in the SC. Such strategies were mainly based on Chowdhury et al. (*12*) and Remko (*22*), in which the authors analyzed previous epidemic events and provided such strategies as opportunities to improve the SC resilience.

Note the existence of exogenous nodes: COVID-19 cases, time, space, and the international declaration of COVID-19 as a global pandemic on March 11, 2020. No global announcement had specific worldwide impacts, because policies were developed locally within each country. To mitigate how other events could have occurred on or around the selected dates, the authors included the variable "time" in the modeling as an exogenous variable, as well as the COVID-19 death rate variable, which included the daily reported and confirmed cases and deaths worldwide. The analyses assumed that "time" and "COVID-19 cases" were variables that would affect all the word- and phrase counts, whereas the declaration of COVID-19 was expected to increase people's anxiety and fear and consequently affect feelings of losing control.

Dictionary Clusters

Figure 9 represents a cluster of words based on the research relationship graph, and each cluster was constructed using a dictionary-based approach (i.e., synonyms and word context) using WordNet (*49*) and other dictionaries. For instance, the seed words for the nodes of anxiety and fear, lack perceived control, purchasing, and utilitarian goods were obtained from Barnes et al. (*4*). However, to obtain the synonyms and phrases for the rest of the nodes, the authors used online dictionaries (e.g., Merriam-Webster). Table 1 shows a sample of dictionary entries. All the terms are intended to be independent and unique for each category, for instance, "anxiety and fear" words are different to those of "lack of perceived control" and to the other clusters. Note that there could nonetheless be certain contexts in a text that could affect the accuracy of the inferences drawn from the analyses. However, the authors implemented a series of approaches to help mitigate this, and to reveal relationships between the articles' contexts and the hypotheses that related to direction of impact. The following points list some of the key approaches used:

- In addition to word dictionaries, the authors developed phrase dictionaries (i.e., constructed phrases from combinations of words, e.g., SC resilience strategies equal SC adaptability plan). As expected, the phrase count was much lower than the dictionaries comprising individual words. We identified patterns and adjusted the counts to reflect potential phrase contexts.
- Sentiment analysis was used to identify potential word (from word dictionaries) combinations that might have conflicting sentiments.
- A random sample analysis was performed to check for conflictive phrases and contexts. None were found. As the sample was small, we cannot rule out that this could happen in certain instances, but would not be prevalent, therefore would be unlikely to negatively affect the results. As will be discussed, the results of the analyses were consistent with the expected relationships.
- Topic analysis was used to identify potential news out of the spectrum of SCs and their relationship with COVID-19, however, because of the systematic search described, the news in the data set generally referred to social- and system effects, and to private impacts.

Modeling Analysis

Having clustered the dictionary-based words and phrases, counts were performed for each article. The relationship analyses assumed that counts could be used as proxies for specific topics, that is, the quantitative variable used in regression modeling to evaluate the hypotheses (H_1 to H_8) and represent the relevance of each cluster/node. Recall that the hypotheses attempted to find the existence of relationships between nodes, that is, identify whether a pair of nodes was positively or negatively related, and determine their contribution.

To identify such relationships, the authors used generalized linear models (GLMs) and generalized linear mixed models (GLMMs) that allow discrete variables to be dependent variables, such as Poisson, negative binomial, hurdle, and zero-inflated models (*4*, *50*). There were five response variables for independent analysis: (i) lack of perceived control (lpc), (ii) purchasing (puch), (iii) stockout retailer (stkt_rtlr), (iv) reduced capacity in the SC (rdcap_sc), and (v) resilience strategies in the SC (rscl_strg_sc). For each of these, the authors estimated one GLM and one GLMM model with COVID death rate and date (time) as exogenous variables and date as a

Table 1. Sample Dictionaries

Cluster	Sample words	Words
Lack of perceived control	Defenseless, defenseless, Defenselessly, defenselessly, Dependent, strung-out, helpless, incapacitated, lost, hopeless, impotent, incapable, incapable(p), incompetent, unequal to(p), unqualified, incompetent person, bungling, ineffective [… and 20 more]	39
Anxiety and fear	Anxiety, anxiousness, concern, fear, fearfulness, fright, afraid, afraid(p), alarm, alert, consternation, dismay, horrify, confusedness, confusion, mental confusion, distraught, overwrought, frantic, phrenetic [… and 42 more]	62
Utilitarian	Utilitarian, useful, cleaner, cleanser, cleansing agent, dry cleaner, domestic, family, home, house, household, functional, in working order(p), running(a), usable, useable, working(a), bundle, packet, practical [… and 47 more]	67
Purchase	Purchase, buy, bargain, deal, bought, cart, customer, transact, acquirement, acquisition, acquire, earn, buying, purchasing, pay for, procure, hoarding, accretion, accrual, accruement [… and 14 more]	34
Stockout	Unattainable, out of stock(p), lacking(p), missing, nonexistent, wanting(a), dearth, deficit, shortage, shortfall, stockout, backorder, unpurchasable, unbuyable, unacquirable, unobtainable, unprocurable, unavailable, unmarketable, unmerchantable [… and 40 more]	60
Retailer	Mart, megastore, superstore, concessionaire, depot, e-tailer, food market, grocery, grocery store, mall, market, marketer, marketplace, mercantile establishment, outlet, plaza, retail merchant, retail store, retailer, sales outlet [… and 10 more]	30
Increase lead time	Increase delay, increase lead time, increase lead-time, increase delivery time, increased delay, increased lead time, increased lead-time, increased delivery time, extended delay, extended lead time, extended lead-time, extended delivery time, augment delay, augment lead time, augment lead-time, augment delivery time, augmented delay, augmented lead time, augmented lead-time, augmented delivery time [… and 54 more]	74
Reduced capacity	Block, blockage, break, capacitive reduction, capacity cuts, capacity not, capacity reduction, closedown, closing, closure, decrease, diminution, [… and 52 more]	64
Reduced capacity of the supply chain	Block of chain of distribution, block of chain of production, block of chain of supply, block of chain of value, block of distribution chain, block of distribution chains, block of distribution channel, block of distribution channels, block of distribution network, block of distribution networks, block of distribution system, [… and 3,125 more]	3136
strategy_supply_risk	Avoid overreliance on single supply, avoid dependency on few supplies, avoid dependency on single factory, avoid dependency on few factories, avoid dependency on single supply, avoid dependency on few supplies, avoid dependency on single factory, avoid dependency on few factories, multiple sources, local near sourcing	10
strategy_demand_risk	Inventory buffering, information sharing, information technology, visibility of demand, transparency of inventory	5

random effect. Note that "*i*" refers to the news article. The equations were as follows:

1. Lack of perceived control (lpc)

$$lackperceivedcontrol_i = \beta_0 + \beta_1 \times anxietyandfear_i + \beta_2 \times date + \beta_3 \times covidrate + \beta_4 \times anxietyandfear:$$
$$\text{pandemic\_announcement} + \mu_0 * date_i + \varepsilon \quad (1)$$

where
count of lpc is the dependent variable;
counts of anxiety and fear (aaf) are the independent variables;
pandemic announcement (Ann_1). pa is equal to 1 from March 11 onwards, and zero otherwise;
β_1 is the relationship between aaf and lpc (expected to be positive);
β_4 identifies whether pa affects consumer lpc (expected to be positive);

β_2 and β_3 represent the relationship of lpc with the date and COVID-19 death rate; and
μ_0 is a random effect.

2. Purchase (purch)

$$purchase_i = \beta_o + \beta_1 \times lackperceivedcontrol_i + \beta_2$$
$$\times lackperceivedcontrol_i : utilitarian_i$$
$$+ \beta_3 \times date + \beta_4$$
$$\times covidrate + \mu_0 \times date_i + \varepsilon \quad (2)$$

where
count of *purch* is the dependent variable,
counts of *lpc* and utilitarian (util) are the independent variables,
β_1 represents the relationship between lpc and purch (expected to be positive), and
β_2 identifies whether util acts as a mediator between lpc and purch (expected to be negative).

3. Reduced LOS (rd_los)

$$reducedlevelservice_i = \beta_o + \beta_1 \times purchase_i + \beta_2$$
$$\times reducecapacitysupplychain_i + \beta_3$$
$$\times resiliencestrategysupplychain_i + \beta_4$$
$$\times reducecapacitysupplychain_i :$$
$$resiliencestrategysupplychain_i + \beta_5$$
$$\times date + \beta_6 \times covidrate + \mu_0 \times date_i + \varepsilon \quad (3)$$

where
word count of rd_los is the dependent variable;
counts of purch, reduced capacity (rdcap_sc), and resilience strategy (rslc_strtg_sc) in the SC are the independent variables;
β_1 represents the relationship between purch and rd_los (expected to be positive);
β_2 represents the relationship between rdcap_sc and rd_los (expected to be positive); and
β_3 identifies whether rslc_strtg_sc acts as a mediator between rdcap_sc and rd_los (expected to be negative).

4. Reduced capacity in SC (rdcap_sc)

$$reducecapacitysupplychain_i = \beta_o + \beta_1$$
$$\times shortagetransportation_i + \beta_2 \times shortageworkers_i$$
$$+ \beta_3 \times shortagesupply_i + \beta_4 \times shortageproducts_i$$
$$+ \beta_5 \times shortagewarehouse_i + \beta_6 \times restrictiontrade_i$$
$$+ \beta_7 \times date + \beta_8 \times covidrate + \mu_0 \times date_i + \varepsilon$$

$$(4)$$

where
count of the *rdcap_sc* is the dependent variable;
counts of shortages of transportation, workers, supply, products, warehouse, and trade restrictions (*shrtg_trnsp*, *shrtg_wrkr*, *shrtg_sppl*, *shrtg_prdct*, *stkt_wh*, and *trade_rstr*) are the independent variables; and
β_1 to β_6 represent their respective relationships with *rdcap_sc*.
All the aforementioned coefficients were expected to be positive.

5. Resilience strategy in SC (rslc_strtg_sc)

$$resiliencestrategysupplychain_i = \beta_o + \beta_1$$
$$\times multiplesources_i + \beta_2 \times strategydemandrisk_i$$
$$+ \beta_3 \times strategycontrolrisk_i + \beta_4$$
$$\times increasesupplychaincapacity_i + \beta_5$$
$$\times technologyinvestment_i + \beta_6 \times date$$
$$+ \beta_7 \times covid_{rate} + \mu_0 \times date_i + \varepsilon \quad (5)$$

where
count of *rslc_strtg_sc* is the dependent variable;
counts of multiple sources, strategies of demand risk, and control risk obtained from Chowdhury et al. (*12*), diversification of suppliers, increase of SC capacity, and technological investment (*mult_sources, strtg_dmnd_rsk, strtg_ctrl_rsk, dvsct_sppl, inncap_sc, tchn_nvst*) are the independent variables; and
β_1 to β_5 represent their respective relationships with *rslc_strtg_sc*.
All the aforementioned coefficients were expected to be positive.

Empirical Results and Discussion

Dictionary Results

Once the dictionaries were revised, cleaned, and validated. The authors created a document feature matrix that counted the number of words/phrases included in each cluster for each article (*51*). A sample of the word counting considered that each row represented an article and each column one node or cluster. Note that one word/phrase was counted as many times as it appeared in one article, and its frequency was assumed to represent a weight or the relevance of the term in the considered article. Also note that there were several variables with compound terms (e.g., *rd_los, rdcap_sc, rslc_strtg_sc*). Let us assume that the count of such variables is the interception of their component counts, obtained by selecting the minimum between both counts for each article, for example,

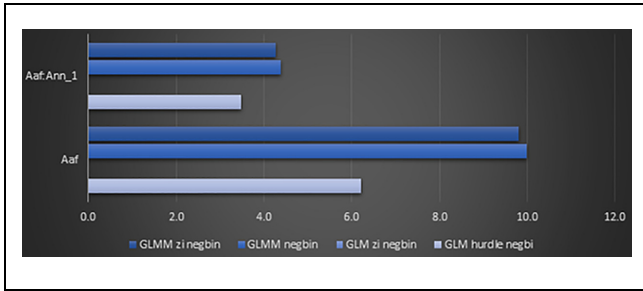$$rslc\_strtg\_sc = min(n(rslc_i), n(strtg_i), n(sc_i))$$

Figure 10. Lack of perceived control coefficients: anxiety and fear (aaf) and pandemic announcement (pa).

where
i = article,
min(.) = minimum function, and
n(.) = count function.
Usually, all the counts have a high density of low count data, many zeros, and large tails, in other words, they are positively skewed. Therefore, the relationship between two counts would be expected to be clustered around the origin. Such behavior shows a linear relationship between variables based on the findings of Barnes et al. (*4*).

Modeling Results

Recall that the counts are discrete variables. Such counts in the news sample the general feeling/situation being faced by the population because news items in the media are openly available and provide information that is known or expected to be true and is widely known by experts. Although it is an arbitrary measure created to implement quantitative regression models, its role is to identify whether the relationships between variables are as expected, and to identify the factors that may affect the performance of the SC, or to evidence opportunities to mitigate the effects of PB behavior.

This section discusses the results of the application of Equations 1 to 5: (1) lack of perceived control, (2) purchase, (3) reduced LOS, (4) reduced capacity in the SC, and (5) resilience strategy in the SC. As stated, there were two models: (i) GLM and (ii) GLMM (considering date/time as the random variable) (Table 2). The GLMs considered in this work included Poisson, negative binomial, hurdle Poisson, hurdle negative binomial, zero-inflated Poisson, and zero-inflated negative binomial; the GLMMs included Poisson, negative binomial, hurdle Poisson, and zero-inflated negative binomial. Following data analysis, the models found to have superior performance were the negative binomial (hurdle and zero-inflated) models. Table 2 gives the results from the models: the first column indicates the variable of the coefficient considered, the following columns comprise the coefficients according to the type of model. The final five

rows in each model show the Bayesian information criterion (BIC), Akaike information criterion (AIC), log-likelihood (LogLik), deviance, and Pearson chi-square. The Pearson chi-square compares the saturated model with the only intercept model. All of them were used to select the best models.

From the data in Table 2 it can be observed that the negative binomial models outperformed the Poisson model across all possible comparisons. For instance, when calculating Pearson's chi-square between the negative binomial and Poisson regression models, the *p*-value was low (i.e., lower than 0.01). The hurdle and zero-inflated negative binomial models were superior in relation to AIC, BIC, deviance and log-likelihood in most of the analyzed models (see Supplemental Material for a detailed analysis of the results). These results were expected because Poisson models underperform when compared with negative binomial models when dispersion is too large, because negative binomial regression has an extra parameter that allows modeling of overdispersion (*52*, *53*). Therefore, negative binomial was used when modeling count data exhibiting overdispersion (*53*). Furthermore, the ability of the hurdle or the zero-inflated models to account for excess zeros gave them an advantage over a count model that could not. Finally, note that the GLMM zero-inflated negative binomial model had the best metrics; this may be interpreted as use of the date as the random effect in such models improving their performance, or as a need to include zero counting in the mixed models. A description of the results for each model using negative binomial regression follows:

- **Lack of perceived control (lpc) model**

In Figure 10 the coefficients of anxiety and fear (aaf) were found to be positive and statistically significant in all the regressions performed. That is, the counts evidenced that when more words/phrases related to anxiety and fear appeared in the news, more words/phrases associated with lack of perceived control also appeared. Therefore, when the number of people feeling anxiety and fear increased, their perceived control decreased because of COVID-19 events, as predicted in H_1. Conversely, "pandemic announcement" with "anxiety and fear" was positively related to lack of perceived control, as expected. The results therefore showed the variable importance given by the Z-value ($Z_{value} = \frac{\beta_i}{se(\beta_i)}$) of the coefficient, the model type, and the distribution.

- **Purchase (purch) model**

Figure 11 shows that the coefficients of the lack of perceived control were positive and statistically significant.

Table 2. Resulting Models for Lack of Perceived Control (lpc), Purchase (purch), Reduced Level of Service (rd_los), Supply Chain Capacity Reduction (rdcap_sc), and Supply Chain Resilience Strategies (strtg_rslc_sc)

Lack of perceived control

Type	GLM		GLMM	
	hurdle_negbi	zi_negbin	negbin	zi_negbin
intercept	**−9.0E+00**	−6.5E-01	**−6.5E-01***	−6.0E-01*
	2.7E+01	9.6E-02	**9.6E-02**	9.9E-02
Aaf	**1.2E-01***	1.0E-01	**9.8E-02***	9.3E-02*
	1.9E-02		**9.8E-03**	9.4E-03
date	**5.8E-04**	−1.3E-04	**−1.9E-04**	−4.9E-05
	1.4E-03		**7.5E-04**	7.7E-04
death_rate	**−2.3E+00**	−2.3E+00	**−2.4E+00**	−2.2E+00
	4.0E+00		**2.2E+00**	2.2E+00
Aaf:Ann_1	**9.7E-02***	5.5E-02	**5.8E-02***	5.3E-02*
(se)	**2.8E-02**		**1.3E-02**	1.2E-02
BIC	**10659**	10751	**10714**	10733
AIC	**10586**	10679	**10668**	10667
LogLik	**−5282**	−5328	**−5327**	−5324
Deviance	**10564**	10657	**10654**	10647
Pearson chi-square	**6.3E-162**	1.1E-179	**7.7E-168**	3.2E-157
Purchasing				
Intercept	**5.99E-01***	9.8E-01*	6.38E-01*	**6.9E-01***
	1.1E-01	6.9E-02	1.0E-01	**1.0E-01**
lpc	**2.2E-01***	2.2E-01*	2.3E-01*	**2.3E-01***
	1.9E-02	1.3E-02	1.3E-02	**1.3E-02**
date	**−1.9E-03****	−1.9E-03*	−1.3E-03**	**4.1E-01**
	7.4E-04	5.1E-04	6.9E-04	**2.1E+00**
death_rate	**−3.1E+00**	−3.5E-00**	5.8E-01	**−1.3E-03****
	2.1E+00	1.5E-00	2.1E+00	**6.9E-04**
lpc:util	**6.2E-05**	−1.7E-04*	−2.8E-04*	**−2.6E-04***
	3.9E-05	3.4E-05	3.6E-05	**3.8E-05**
BIC	**20868**	21031	20915	**20935**
AIC	**20795**	20959	20869	**20870**
LogLik	**−10387**	−10468	−10428	**−10425**
Deviance	**20773**	20937	20855	**20850**
Pearson chi-square	**4.5E-193**	3.6E-264	1.0E-200	**1.8E-199**
Level of service				
intercept	**−2.0E+00***	−1.1E+00*	−1.7E+00*	**−1.1E+00***
	3.0E-01	1.3E-01	1.1E-01	**1.2E-01**
purch	**5.5E-02***	3.7E-02*	6.9E-02*	**3.7E-02***
	8.4E-03	4.2E-03	5.5E-03	**4.2E-03**
rd_cap_sc	**1.4E-01***	1.3E-01*	1.8E-01*	**1.3E-01***
	2.1E-02	1.4E-02	1.6E-02	**1.4E-02**
strtg_rslc_sc	**3.0E-01***	2.7E-01*	2.3E-01*	**2.8E-01***
	8.9E-02	5.7E-02	5.5E-02	**5.7E-02**
date	**4.5E-04**	1.4E-04	1.1E-03	**1.0E-03**
	1.3E-03	8.9E-04	7.7E-04	**7.8E-04**
death_rate	**8.1E+00****	7.2E+00*	5.4E+00**	**5.5E+00****
	3.7E+00	2.6E+00	2.2E+00	**2.2E+00**
rd_cap_sc:strtg_	**−2.3E-02***	−2.2E-02*	−2.7E-02*	**−2.2E-02***
	8.2E-03	5.3E-03	5.8E-03	**5.3E-03**
BIC	**9066**	9069	9162	**9048**
AIC	**8968**	8970	9103	**8962**
LogLik	**−4469**	−4470	−4542	**−4468**
Deviance	**8938**	8940	9085	**8936**
Pearson chi-square	**5.5E-230**	1.4E-247	9.6E-208	**8.7E-158**
Supply chain capacity				
(Intercept)	**−4.1E-01***	1.3E-01**	**1.1E-01****	1.5E-01**
	1.1E-01	5.8E-02	**5.6E-02**	5.9E-02
shrtg_trnsp	**7.1E-02****	7.8E-02*	**8.0E-02***	7.2E-02*

Table 2. (continued)

Lack of perceived control

Type	GLM		GLMM	
	hurdle_negbi	zi_negbin	negbin	zi_negbin
	3.6E-02	2.1E-02	2.2E-02	2.2E-02
shrtg_wrkr	9.8E-03	−1.3E-02	−3.3E-03	−7.0E-04
	3.6E-02	2.2E-02	2.2E-02	2.2E-02
shrtg_sppl	3.4E-02	3.2E-02	3.3E-02	3.0E-02
	3.8E-02	2.2E-02	2.2E-02	2.2E-02
trade_rstrt	6.6E-02*	5.0E-02*	5.2E-02*	5.2E-02*
	8.1E-03	4.8E-03	5.0E-03	4.8E-03
shrtg_prdct	1.0E-01*	8.4E-02*	8.0E-02*	7.6E-02*
	2.7E-02	1.6E-02	1.7E-02	1.6E-02
stkt_wh	−3.5E-02	−3.4E-02**	−3.9E-02**	−3.5E-02**
	3.0E-02	1.8E-02	1.9E-02	1.8E-02
date	−2.3E-03*	−1.5E-03*	−1.9E-03*	−1.8E-03*
	8.1E-04	5.1E-04	4.7E-04	4.7E-04
death_rate	2.1E-01	−1.6E+00	−1.6E+00	−1.7E+00
	2.1E+00	1.3E+00	1.3E+00	1.3E+00
BIC	14626	14771	14733	14746
AIC	14501	14646	14660	14661
LogLik	−7231	−7304	−7319	−7317
Deviance	14463	14608	14638	14634.5
Pearson chi-square	3.0E-212	7.8E-251	5.0E-234	3.9E-229
Supply chain resilience strategies				
Intercept	−4.5E+00	−2.9E+00*	−3.6E+00*	−2.8E+00*
	5.0E+00	2.5E-01	1.9E-01	2.1E-01
dvsfct_sppl	2.2E-01*	2.0E-01*	2.6E-01*	1.5E-01*
	5.2E-02	2.7E-02	3.0E-02	2.3E-02
tchn_nvst	−7.5E-02	1.6E-01*	2.5E-01*	5.0E-02
	1.0E-01	5.0E-02	5.0E-02	4.6E-02
inccap_sc	7.8E-01**	4.4E-01**	4.3E-01**	3.3E-01**
	3.7E-01	2.1E-01	2.0E-01	1.7E-01
mult_sources	2.4E-01	−8.6E-04	−6.7E-02	1.7E-01
	4.4E-01	2.2E-01	2.6E-01	2.1E-01
strtg_dmnd_rsk	−9.4E-03	1.2E-01	2.4E-01	2.2E-01
	4.4E-01	2.0E-01	2.2E-01	2.0E-01
strtg_ctrl_rsk	1.3E-01**	1.1E-01*	1.4E-01*	1.1E-01*
	6.3E-02	2.8E-02	3.2E-02	2.7E-02
date	4.7E-03**	4.9E-03*	7.2E-03*	6.6E-03*
	2.4E-03	1.7E-03	1.1E-03	1.1E-03
death_rate	7.7E-01	1.2E+01*	1.4E+01*	1.3E+01*
	7.8E+00	4.7E+00	3.5E+00	3.5E+00
BIC	4520	4524	4481	4447
AIC	4395	4399	4409	4355
LogLik	−2179	−2181	−2193	−2164
Deviance	4357	4361	4387	4327
Pearson chi-square	4.1E-81	2.5E-81	1.3E-67	6.6E-34

Note: GLM = generalized linear models; GLMM = generalized linear mixed models; BIC = Bayesian information criterion; AIC = Akaike information criterion; LogLik = log-likelihood.
GLM and GLMM (hurdle, zero-inflated, negative binomial).
$^*p < 0.01$; $^{**}p < 0.05$.

As stated, H_2 posited that when people lack perceived control they buy more; the counts showed that when the lack of perceived control increased so did the number of purchases. Additionally, utilitarian goods were found to
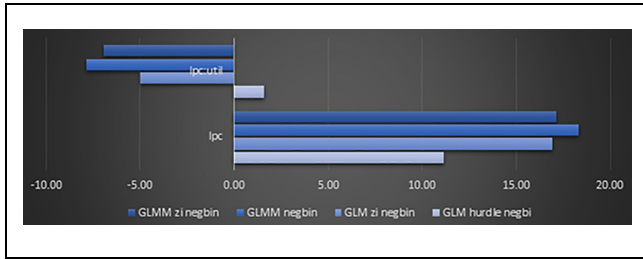
Figure 11. Purchase coefficients: lack of perceived control (lpc) and utilitarian goods (util).
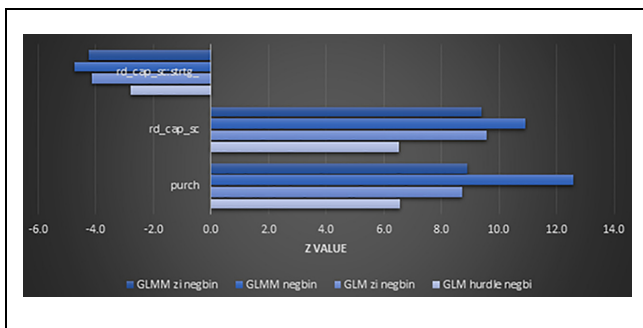

Figure 12. Reduced level of service coefficients: reduced capacity in the SC (rd_cap_sc), purchase (purch), and resilience strategy in the SC (strtg_rslc_sc).
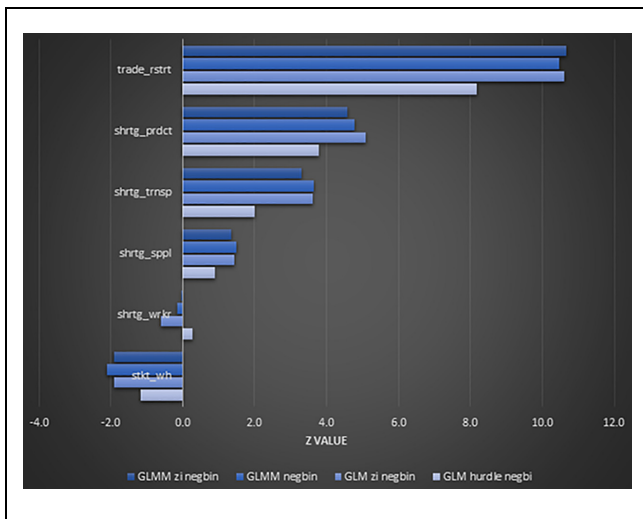

Figure 13. Reduced capacity SC coefficients: shortage warehouse (stkt_wh), product (shrtg_prdct), supply (shrtg_sppl), workers (shrtg_wrhr), transportation (shrtg_trnsp), and trade restriction (trade_rstrt).

function as a mediator between lack of perceived control and purchasing because their interaction reduced the level of purchases (i.e., as hypothesized in H_3, because utilitarian goods give a feeling of control to consumers).

The results from H_1 to H_3 were consistent with the findings of Barnes et al. (4) who used Twitter data.

- **Reduced LOS (rd_los) model**

In Figure 12, purchase and reduced capacity in the SC had positive coefficients, indicating that an increase in purchases and the prevalence of problems in the SC were related to the reduction in capacity and consumers perceiving a reduction in the LOS—confirming H_4 and H_6, respectively. Conversely, resilience strategies in the SC (rslc_strtg_sc) helped to mitigate the reduced capacity in the SC (rdcap_sc) because their interaction diminished the reduction in the LOS as posited by H_5. The results of the rdcap_sc and rslc_strtg_sc models provided insights into the most critical issues related to the reduction of the capacity of the SC, as well as the most widely used strategies to increase resilience based on the media.

- **Reduced capacity in the SC (rdcap_sc) model**

Figure 13 shows that most of the coefficients were positively related to the reduction of the capacity in the SC, except for warehouse shortages. The model indicated the positive implications of such shortages in the reduction of the capacity in the SC, as anticipated by H_7. For instance, note that trade restrictions had the highest impact on the reduced capacity in the SC across all models. Trade restriction played an important role in SC capacity reduction because such measurements forced some manufacturers to reduce or stop production altogether during the pandemic (54) and/or exacerbated their production and distribution capabilities (55). Another key issue related to reduced capacity of the SC was shortage of products and transportation. Note that the flow and movement of goods are highly dependent on the availability of the aforementioned factors. That does not mean that workers, supply, and warehouse shortages were not related to reduction in the capacity of the SC, but that the media in our sample had not widely discussed those issues.

- **Resilience strategy in the SC (rslc_strtg_sc) model**

Figure 14 shows that most of the strategies were positively related to resilience strategy in the SC. The model showed the positive implications of such strategies as hypothesized by H_8. Among the strategies, diversification of suppliers had the highest importance in relation to resilience strategy in the SC. Note that this result is in line with research undertaken by Harapko, in which 24% of 200 senior-level SC executives surveyed in 2020 considered the diversification and segmentation of suppliers' strategies to be one of the Top 10 priorities for the
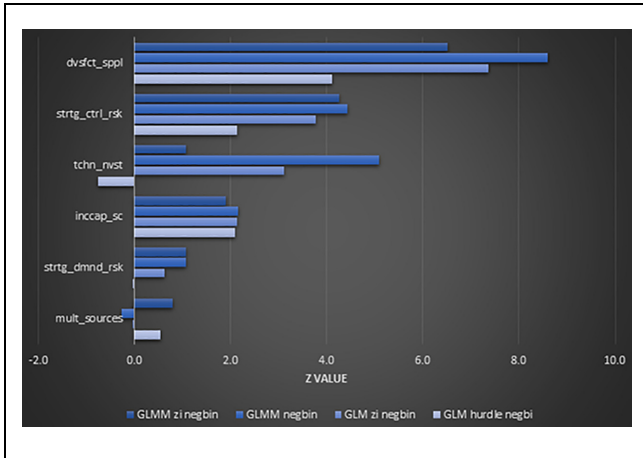
Figure 14. Resilience SC coefficients: strategy control (strtg_ctrl_rsk), demand (strtg_dem_rsk), multiple sources (mult_sources), increased capacity (nkcap_sc), technological investment (tchn_nvst), and diversification of suppliers (dvsfct_sppl).

coming 12 to 36 months (*56*). Such a strategy was an aspect of all the dimensions of resilience (*12*): preparedness, response, and recovery of the SC. By diversifying suppliers, the SC could avoid production breakdowns when a certain location was put in lockdown (*22*). Despite the advantages, this strategy requires a redesign of the SC and associated logistics, a challenging but crucial step in the improved resilience of an SC. Diversification of suppliers was followed by control strategies, such as negotiating with bottleneck suppliers, negotiating savings with selected suppliers, prioritization, and service innovation. These were highlighted by Chowdhury et al. (*12*) as having a significant role in the improved resilience of an SC. Harapko considered technological investment to be the main strategy for SCs in the future (*56*). A capacity increase in the supply follows in importance based on the model. However, 65% of SC executives surveyed by Harapko believed an increase in efficiency was the most viable strategy in the middle of a disruption (*56*). Note that most of the resilience strategies were more related to SC reengineering strategies, for example, design and sourcing; however SC resilience strategies related to agility and greater visibility and velocity in the SC were lacking (*57*). Therefore, exploring alternative resilience strategies is necessary.

In Figure 15, note that time (date) and COVID-19 death rate (death_rate) performed differently in the models. For instance, for lack of perceived control, purchase, and reduced capacity in the SC the death rate was not statistically significant ($\alpha = 0.05$), whereas most of the models in resilience strategy in the SC and reduced LOS seemed to be statistically significant and positively related. This indicated that the greater the mentions of COVID-19 death rate, the higher the counts for resilience strategies and reduction of LOS. In relation to time, reduction in the capacity of the SC, and purchase tended to decrease with time, whereas resilience strategies of the SC tended to increase with time in most of the models. This suggests that at the beginning of the pandemic journalists were more interested in informing the public about SC issues and demand spikes, but such counts diminished over time when counts of SC resilience strategies tended to increase. The behavior of this set of variables was in line with the results obtained by the reduced LOS (rd_los) model, in which the increases in demand (purchase), and supply (reduced capacity in the SC) were opposite to the increases in SC resilience strategy in the reduced LOS.

Key Findings and Conclusions

The results from the empirical analyses of news between February 2020 and July 2020 were consistent with earlier studies about the behavior of consumers in the relationship between anxiety and fear, lack of perceived control, and purchasing. Additionally, the results were coherent with the expected behavior when analyzing consumer buying behavior, SC issues, and opportunities with respect to the reduction in the perceived LOS of the SC. The results provide a range of insights, listed below.

- The results of the lack of perceived control and purchase model confirmed that lack of perceived control (lpc) was related to consumer anxiety and fear (aaf). The effect of the lack of perceived control generated by the anxiety and fear of consumers might have created the need for purchasing products. This may be one of the explanations for the spike in demand provoked by precautionary and opportunistic buying. However, buying utilitarian goods gave consumers back a sense of control that was beneficial, as explained in Barnes et al. (*4*). Additionally, our models found meaningful relationships between precautionary and opportunistic buying behavior and time. Note that the peak of such purchase words occurred at the beginning of the pandemic and then started to fade (see Figure 7).
- The reduced LOS (rd_los) model confirmed that the demand from the increase of purchasing, and the reduction of the capacity in the SC prompted by restrictions and shortages were positively related to reduced LOS (rd_los). However, resilience strategies in the SC played a significant role in mitigating the effects of SC capacity reduction toward a reduction in LOS.
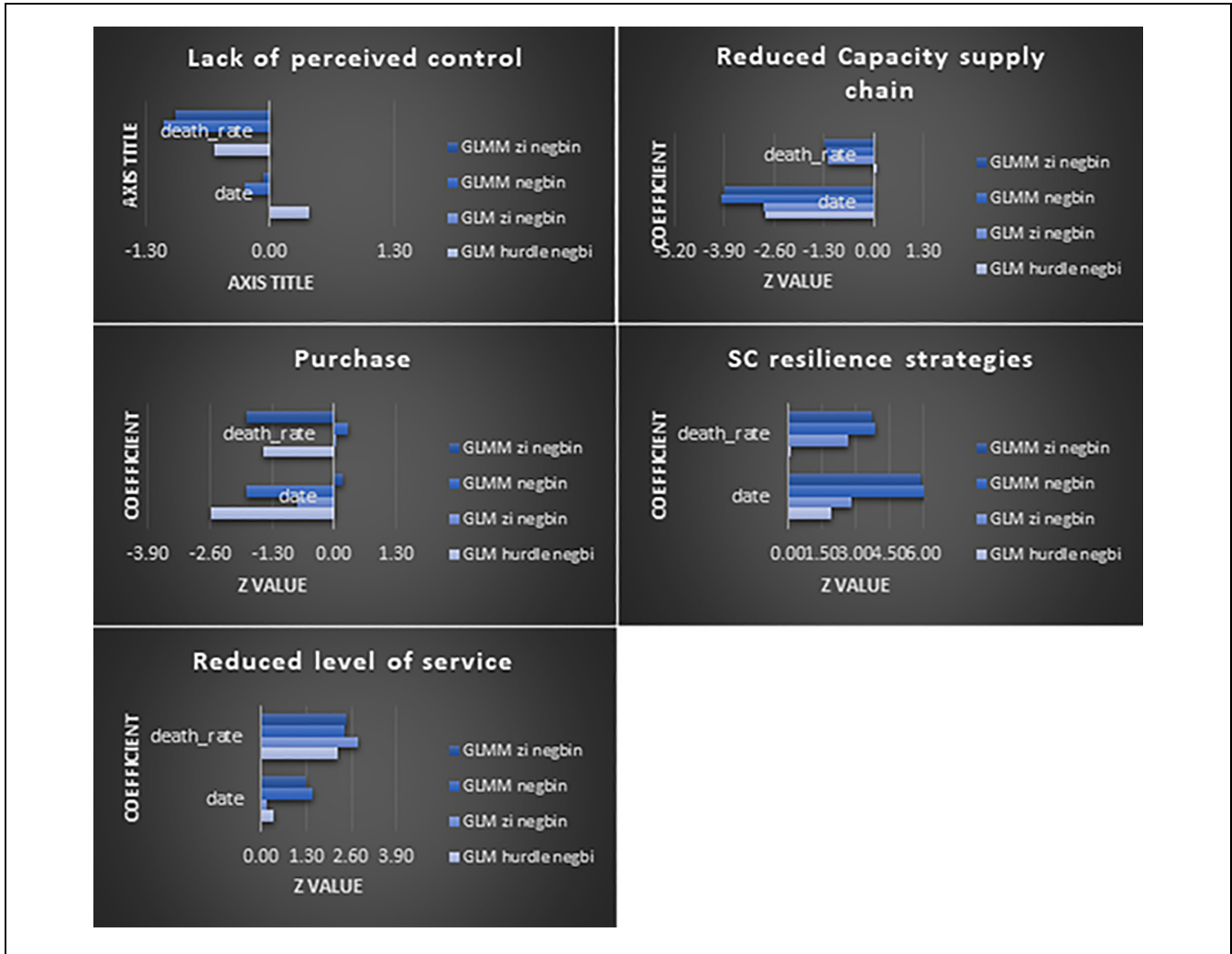
Figure 15. Influence of time and death rate on models.

○ Note that trade restrictions was the principal factor in SC capacity reduction. This result was coherent given the impact of those trade restrictions on the global SC (*54*).

○ Among the strategies obtained in the resilience strategy in the SC model, diversifying suppliers was rated as the most important strategy. This strategy is endorsed as one of the Top 10 strategies to be implemented by SC managers (*56*). Technological investment (e.g., investing in automation) was also positively rated, as was increasing the capacity of the SC. However, for the majority of SC executives surveyed by Harapko, increasing efficiency was a more highly accepted strategy than capacity increase, which makes more sense under a disruption situation such as COVID-19 (*56*). Additionally, let us remark on the importance the control strategies in the SC obtained the

model that considers negotiating with bottleneck suppliers, negotiating savings with selected suppliers, prioritization, and service innovation such as enhancing business e-commerce capabilities by allowing online sales and providing home delivery. Given that this study was based on specified resilience strategies, it lacks exploration of alternative strategies. However, it is worth noting that such strategies are those mostly frequently used on SC resilience improvement according to the literature (*12*, *22*).

• COVID-19 death rate and time played important roles in the behavior of the models. For instance, the COVID-19 death rate was related to the reduced LOS and resilience strategies in the SC models. Resilience strategy counts increased with time, whereas the counts of reductions in the

capacity of the SC and purchase decreased with time.

- Demand management played a key role during precautionary and opportunistic buying behavior. A strategy found in the literature was rationing the number of products per consumer, not only to avoid spikes in the demand of products, but also to hamper hoarding behaviors, and allow more people to access these goods. However, it would be interesting to identify exactly when such rationing should start. What events might detonate the anxiety and fear, lack of perceived control, and catastrophic PB?

Overall, the results of this study were in line with those of other studies related to PB and to SC resilience (4, 12). The methodology and the analysis of their relationship allowed us to evaluate the interactions between multiple factors. Overall, the results confirmed that buying behaviors and the reduction in the capacity of the SC led to a lower LOS perceived by consumers, however, resilience strategies were able to mitigate the impact of capacity reductions in the SC.

It is worth noting that this research had some limitations, such as the use of data from news items, the design of hypotheses that may have omitted other important factors and relationships, the selected sample in relation to date period, and shortcomings in the text analysis tools, which may not always have identified the contexts in which the words and phrases appeared in the text. Despite these limitations, the empirical analyses has shown that the proposed approach, using data extracted from the news, could represent and identify impacts consistent with expectations from the SC field under disruptions, and could also quantify the magnitude of the impacts as the pandemic evolved, providing more information for decision making. Although there may be limitations to using news items, the authors believe that, at least conceptually, this can provide access to a large net of experts, as news usually involves fact-checking and reporters interviewing people on the ground. It is true that there could be misinformation in the press and media, but gathering data from multiple sources within different geographies could help mitigate such issues. The data and analyses in the methodology portrayed how different topics showed different patterns over time, providing opportunities for these to be used in real-time to identify such trends and potentially anticipate impacts as a disruption evolves. Additionally, the method of using historic information could help to develop forecasting tools for impacts distributed throughout time and space. Nevertheless, further research is needed to directly identify the impact of resilience strategies on the SC and to understand how distinct types of SCs are affected by pandemics.

ORCID iDs

Daniel Rivera-Royero ⓘD https://orcid.org/0000-0003-2137-5664

Miguel Jaller ⓘD https://orcid.org/0000-0003-4053-750X

Alan Jenn ⓘD https://orcid.org/0000-0003-4232-0697

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