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Resilience and Recovery: Understanding the Underlying Drivers of Long-term Instability in Food Supply Chains

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Abstract

The risk of disruption to a supply chain can be explained as any incident that negatively affects a business's operations and is typically short-term and localized due to crises. There is scarce information on extended and global supply chain disruptions (SCD) impacting supply chain (SC) stability. The paper aims to use regional census data from a prominent food production company to identify and quantify the drivers of instability during a long-term disruption. This research uses multivariate control charting methodologies, data mining, and feature analysis to determine how geographical, demographic, and product characteristics impact SC stability.

Keywords: food supply chain resilience, feature analysis, multivariate control chart methodology

Introduction

The motivation behind this study stems from the significant challenges presented by the COVID-19 pandemic and its wide-ranging effects on the global supply chain. Although much research has been done on the supply chain (SC) risk management topic, there is no universally accepted

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definition and classification for supply chain disruptions (SCD) and risk sources. Generally, SC risks can be categorized into natural disasters like hurricanes, earthquakes, outbreaks of epidemics, and man-made disasters like terrorist acts, political instability, and labor strikes; also, the nature of the disruption, high frequent-low impact vs. low frequent-high impact, is critical to resilience strategies.

Among the risks mentioned above threatening the SC, widespread public health incidents like outbreaks deserve precise attention for business decisions due to their distinct characteristics. Typically, outbreaks impose both short- and long-term disruptions that adversely impact the firm's efficiency and performance (Sodhi, 2016; Guan et al., 2020; Ivanov, 2020), and as disturbance propagates beyond its origin and across the entire SC network, known as the ripple effect, it negatively impacts the firm's resilience and sustainability (Ivanov and Dolgui, 2020b).

Unlike any other epidemics that SCs encountered in recent years, such as the SARS epidemic in late 2002 or the H1N1 epidemic in early 2009, the coronavirus pandemic (COVID-19) is a notable example of disruption in the SC due to its multidimensional characteristics. It was not limited to a specific region or time and held more intense and dynamic features, affecting all the SC members (Chowdhury et al., 2021).

Although purchasing behavior is a complex and dynamic process, the severe impact of the COVID-19 pandemic on SCs greatly affected consumers' buying patterns and behavior (Hasan, Islam, and Bodrud-Doza, 2021). On the one hand, stressed SCs suffered from delays in delivering products to customers, which in the food SC caused food security concerns (Ivanov and Dolgui, 2020a; Siche, 2020), and the ability of SCs to provide needed products became a critical topic on the evening news and 24-hour news cycle.

On the other hand, the visible shortages of products, the perception of product scarcity, and the inability to predict and estimate the level of disaster generated uncertainty in communities and contributed to the competition for limited resources and hoarding behavior (Tukachinsky Forster and Vendemia, 2021). Seen explicitly in healthcare-related and food products, panic buying and stockpiling drove unforeseen demand spikes (Barneveld et al., 2020; Deaton and Deaton, 2020; Hobbs, 2020; Richards and Rickard, 2020; Paul and Chowdhury, 2021). An unfortunate result was increasing public concern about the food SC instability and resiliency (Hobbs, 2020), food security (Deaton and Deaton, 2020; Siche, 2020), and food waste (Dente and Hashimoto, 2020; Sharma et al., 2020) as the pandemic worsened.

Chowdhury et al. (2021) revealed that most of the evaluated studies investigated "disruptions in each area/function of a supply chain in isolation" (p. 16), which is in line with the frequent short-term nature of the previous disruptions. However, the recent pandemic profoundly impeded the global SC, allowing the opportunity to investigate the factors that drive SC instability over intermediate and extended periods and build foundations for improving the performance of the SC under long-term crises. Using large data sources, feature extraction/mining, multivariate factor analysis, and analytics, this paper's primary goal is to analyze and understand the factors that contribute the most to the instability of the food SC network under a pandemic with long-term and global impact. This analysis will contribute to SC resilience and disruption theory by evaluating the impacts of geography, economic indicators, and population on the instability of the stressed food SC network. In addition, the result of this study will help supply chain and distribution leaders prepare for future disruptions.

The rest of the paper is organized as follows. The Literature Review section explores the SCD and consumer behavior literature. The Data and Methodology section describes the study data and the methodology used to analyze instability and causality. The Findings and Discussion section illustrates the results of our analysis, and the Conclusions and Future Research section offers the resulting theoretical and managerial implications and future research directions.

Literature Review

Supply Chain Disruptions (SCD)

SCDs are common and frequent and pose high levels of risk that affect enterprises' performance (Blackhurst et al., 2005; Gunasekaran, Subramanian, and Rahman, 2015; Chen, Das, and Ivanov, 2019). SCDs are unplanned and unanticipated interruptions in the typical SC flow continuity with a negative impact (Craighead et al., 2007; Xu, 2008). Examples include a lightning strike at the Philips NV Microchip plant in New Mexico (2001), the 9/11 terrorist attack (2001), the SARS outbreak (2003), Hurricane Katrina (2005), the Ebola outbreak (2008), the housing market depression (2008), the Eyjafjallajokull volcano (2010), the Japanese tsunami (2011), and the Evonil chemical plant fire in Germany (2012).

We recognize that SC networks are becoming more global and interconnected (Blackhurst et al., 2005; Chen et al., 2019) in the way that local events can have a global impact, although not at the scale and length of disruptions seen starting in 2020. The COVID-19 pandemic differed from past disruptive events both in scope and duration.

Economic challenges, performance effects, financial losses stemming from sales, loss of jobs, unavailable resources, insufficient raw materials, and negative impacts on shareholder wealth and operating performance are some of the adverse effects of SCDs. These events often lead to many firms declaring bankruptcy due to insufficient preparation for the SCD (Macdonald and Corsi, 2013). Although globalization aids in minimizing costs and increasing economic profit, disruptions increase the global vulnerability to risk and uncertainty by increasing dependency and limiting local flexibility (Christopher and Peck, 2004).

In response to supply chain disruptions and their severe impacts, companies can restore their operations by employing resilience, agility, collaboration, redundancy, hardening, and flexibility, depending on the context, location, and severity of the disturbance (Zsidisin and Wagner, 2010). Resilience is often associated with dynamic capabilities, referring to an organization's ability to adapt and reconfigure processes and resources in response to environmental changes and turbulence (Teece, Pisano, and Shuen, 1997).

Most previous disruptions, such as hurricanes, tornadoes, tsunamis, and earthquakes, were relatively short-lived, lasting less than three months. However, a few supply chain disruptions, such as Y2K and epidemics like Ebola, SARS, and pandemics, had longer-lasting impacts. The COVID-19 pandemic is a notable example of an enduring and highly challenging period for businesses globally. Therefore, it becomes crucial to comprehend the effects of an extended SCD timeframe on firms' operational capabilities and their responses to risk management.

Consumer Behavior and Demographic Factors

Consumer behavior is a multidisciplinary notion that incorporates studying all related activities to purchasing, consuming, and disposing of goods and services. It can be defined as the actions taken by individuals who directly obtain economic goods and services, along with the decision-making process that guides these actions. (Engel, Blackwell, and Miniard, 1986).

Consumer behavior is one of the well-studied phenomena in the marketing field. It is rooted in the theory of reasoned action (TRA), suggested by Fishbein and Ajzen (1975), and the theory of planned behavior (TPB) (Ajzen, 1991), which note that consumer behavior is influenced by different factors such as the individual's beliefs, subjective norms, and attitude. The main goal of consumer behavior studies is to understand people's wants and decision-making process via three major approaches: psychographics, consumer typology, and their characteristics (Yousaf and Huaibin, 2013). Accordingly, some scholars (Fisher, 1951; Lydall, 1955; Zwick, 1957; Pol, 1991; Lee, 2005) have studied the effects of the consumer's demographic characteristics like gender, age, ethnicity, income, and educational level on the consumer's purchasing decision process, and others analyzed the impacts of external issues, such as economic crises and natural disasters on consumers' purchasing behavior (Wen, Gu, and Kavanaugh, 2005; Filip and Voinea, 2011; Levine and Shin, 2018).

Scholars recognized fear, anxiety, depression, loss, guilt, irritability, isolation, and stigmatization as the general psychological reactions to disease outbreaks (Omar et al., 2021). Also, they showed that demographic factors are associated with fear, panic, anxiety, and stress (Alfuqaha et al., 2022).

The rise in global crises over the past decade has led to an increase in research studies examining the impact of scarce resources and stressful situations on consumer behavior, "triggered by the 2008 financial crisis, and likely to be accelerated by scarcity related to the COVID-19 global pandemic" (Pol, 1991; Goldsmith, Griskevicius, and Hamilton, 2020).

Omar et al. (2021) identified that during COVID-19 consumer buying behaviors were influenced by uncertainty, perceived severity, perceived scarcity, and anxiety. Moreover, panic buying behavior is one of the expected responses to the fear of scarcity and anticipated regret of a missed opportunity (Chua et al., 2021). Literature links the perception of scarcity and demographic factors, such as age, employment status, experience, income level, and marital status, with panic buying behavior (Wang, Shen, and Gao, 2018; Arafat et al., 2020; Li et al., 2021). By employing the react-cope-adapt (RCA) model, Kirk and Rifkin (2020) showed that hoarding behavior and rejecting behavioral mandates are two reactions that consumers may show to the perceived scarcity and regaining control of lost freedoms.

Crosta et al. (2021) found that during the COVID-19 pandemic, consumer purchasing behavior differed depending on the product categories essentials vs. nonessentials. Duygun and Şen (2020) explained that people have the propensity to purchase essential products like food, beverages, shelter, and clothing to satisfy their physiological needs. Baker et al. (2020) revealed a significant increase in household expenditures for essentials and food products. Schmidt, Benke, and Pané-Farré (2021) reported growth in purchasing nonperishable food and hygiene products. Sidor and Rzymski (2020) revealed the changes in consumer dietary habits and consumption patterns during the pandemic lockdown in Poland. These findings confirm that the crisis caused by the COVID-19 pandemic is a long-lasting and fundamental phenomenon with global societal and economic impacts.

In addition, analyzing the relationship between consumer purchasing behavior and SC challenges is not a new subject; however, the impact of consumer behavior and purchasing patterns during the COVID-19 pandemic on the food SC, in particular, has been unattended to by scholars and practitioners. Hence, it is crucial to reconsider and understand the effect of the consumer's demographic factors on purchasing behavior during an extended global crisis for supply chain decision makers and managers to design necessary strategies.

Data and Methodology

Data Description

Our data are from a large multinational food producer that manufactures and distributes staples and nonessential snacks to retailers and restaurants in North American countries. The data comprise a census of all 2019 and 2020 wholesale-to-wholesale orders and shipments for the United States Midwest region. We selected this period to understand how a long-term disruption (COVID-19) affected this manufacturer's SC before and during the pandemic.

Because the data are a census representing an entire population, the analysis was approached without working assumptions and sampling. Based on the authors' best knowledge, there is no research publication analyzing a global, extended pandemic that specifically addresses instability and distribution.

As a result, an inductive method, grounded theory, was used to approach this extensive dataset (Strauss, 1998; Eisenhardt, Graebner, and Sonenshein, 2016) to allow the theoretical implications of the data to emerge through analysis rather than using deductive methods with preconceived theory. This deep dive into archival data enabled the authors to examine and capture essential aspects of the focal phenomenon (Eisenhardt, Graebner, and Sonenshein, 2016). The grounded theory approach promoted ongoing analysis to drive additional data collection within the company through interviews to develop clearer constructs and better knowledge of relationships and associated processes (Eisenhardt, Graebner, and Sonenshein, 2016). This approach aimed to derive theory from data that resembles reality (Strauss, 1998).

We used a big data approach to understand SC dynamics in this extended disruption. The data come from proprietary ERP (Enterprise Resource Planning) information for all product lines. The raw data contained 22 features and 6,451,370 observations (including headers and empty ERP-generated lines). Each observation was a product request from 385 regional distribution centers (DCs) to five fulfillment hubs. After data cleaning, each of the 6,047,137 observations contained the numerical and classification features shown in Table 1. No observations were missing any feature data. The orders comprised 457,213,759 pallets consisting of between 55 to 60 million tons of product. Although the number of items on these standard shipping pallets (1.066 meters square) varies, each pallet is counted as a standard unit for analysis. Total orders account for roughly 22 billion delivery boxes.

Table 1. Summary of Midwest U.S. Wholesale-to-Wholesale Distribution Data

Feature	Definition	Feature Description (6047137 observations)	Categorical Levels
From entity	From a distribution center	Categorical	Levels = 5
To entity	To a distribution center	Categorical	Levels = 385
Sales date	The date on which a transaction occurred	Categorical	Levels = 658
Product name	The name of the product	Categorical	Levels = 524
Brand level 3 name	Products families	Categorical	Levels = 33
Ordered units	The quantity of requested units	Continuous	Integer
Shipped units	The quantity of shipped units	Continuous	Integer
Shipping adds	The quantity of units exceeding the requested amount	Continuous	Integer
Shipping cuts	The quantity of units reduced from the requested amount	Continuous	Integer
Claims	The quantity of damaged, returned, stolen units	Continuous	Integer
Received units/deliveries	The quantity of received units	Continuous	Integer

To better tie the distribution data to communities, we used a mapping API to identify each entity's latitude, longitude, county, and state data fields. Based on this information, we merged county data using U.S. Census data (projected data through 2020) and current unemployment data from the U.S. Bureau of Labor Statistics (U.S. Department of Commerce, 2021).

Of the 524 products made by the company, there are 33 product families. We deleted five product families due to having less than 100 observations. For analysis and clustering, we explored groupings of the data comparing purchase cost (high/low) and consumption pattern of food type (snacks, staples, and comfort foods).

The data were not severely imbalanced, negating the need for over or under-sampling when using our analysis methodologies. In addition, there was an ordering pattern where Mondays had the highest and Wednesdays had the lowest ordering values used for reconciliations. Therefore, we aggregated orders per week for analysis to reduce day-to-day noise. Once aggregated, we looked at pairwise correlation and checked for autocorrelation. There was little evidence of extensive autocorrelation in any of the variables. Our analysis indicated the data had minimal autocorrelation by using ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function). Table 2 shows the correlation matrix between time-aggregated (week-to-week) variables. Additionally, an unsurprisingly high correlation among ordered, shipped, and received units was found, and a varying correlation among other numerical features was observed, indicating a possible temporal feature correlation.

Table 2. U.S. Midwest Correlation Matrix between Time-Aggregated (Week-to-Week) Variables Using Pearson's Correlation Coefficients)

	Received Units/Deliveries	**Claims**	**Shipping Cuts**	**Shipping Adds**	**Shipped Units**	**Ordered Units**
Received units/deliveries	1.00	0.09	-0.03	0.12	0.99	0.88
Claims	-0.09	1.00	0.04	0.02	0.04	0.03
Shipping cuts	-0.03	0.04	1.00	0.01	-0.03	-0.25
Shipping adds	0.42	0.02	0.01	1.00	0.43	0.01
Shipped units	0.99	0.03	-0.02	0.43	1.00	0.88
Ordered units	0.88	0.03	-0.25	0.01	0.88	1.00

In Figure 1, we show the assignment of DCs to fulfillment hubs. The overlaps among regions occur because drivers have the opportunity to purchase routes from the producer. For the anonymity of the producer, we do not add the location of the regional fulfillment hubs.

Regional Distribution Center Assignment

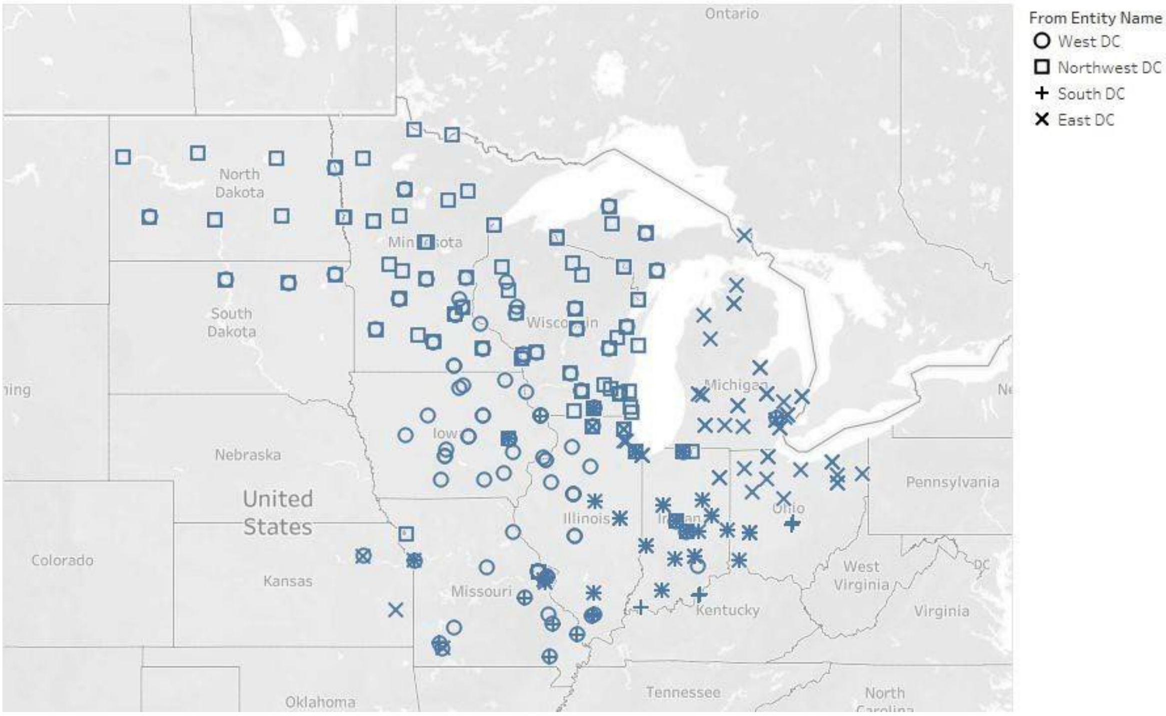

Figure 1. U.S. Midwest Wholesale Distribution Map of the Food Producer

To evaluate the progression of the pandemic, the SC's response, and to consider specific events that impacted consumption in the United States during the pandemic, we divided 2020 into three separate phases, each starting with the following circumstances:

Phase 1: Disaster onset (January 20, 2020—CDC confirms first U.S, COVID-19 case)

The first confirmed COVID-19 case in the United States was reported in Snohomish County, north of Seattle. In the next few weeks, the number of infected people in the United States increased significantly as the disease spread rapidly in other parts of the country. As a result, multiple cities and states had to enforce closures of businesses, schools, and public areas to slow the spread of the virus (Stein, 2020).

Phase 2: First adjustment (April 16, 2020—White House announces gating criteria to reopen economy)

During this time, the White House released a comprehensive plan for returning to work, church, restaurants, and other venues. The plan summarizes the concept of gating criteria, which call for states or metropolitan areas to achieve standards in reducing COVID-19 cases or deaths before moving toward the next step for reopening (AJMC, 2021).

Phase 3 Long-term recalibration (July 2, 2020—states reverse reopening plans)

Governors in several states, like Washington, California, Florida, and Texas, postponed or reversed some of their reopening plans as coronavirus cases rose in more than 30 states across the country, and the United States recorded 50,000 new cases of COVID-19, the most significant one-day spike since the pandemic's onset.(Higgins-Dunn, 2020)

Consequently, while we analyzed the entire 2020 period versus 2019, we also examined the specific pandemic windows to examine for pre-pandemic differences; the windows show observably unique demand phases during 2020.

Table 3 presents state-by-state data for claims, shipment from facilities, total deliveries to the targeted facilities, shipping cuts, and shipping adds across the Midwest United States from 2019 to 2020.

Given the significant increase in orders across the region, the company surged deliveries by 22% during Phase 1. However, increased shipments are concentrated in urban centers and markets close to the regional DCs. While this research does not look at causative effects, we theorize that because in rural America there was a significant disparity between the way Covid was perceived and the actual reality (Weber, 2021), and in early 2020, rural areas did not quarantine to the same levels as places closer to urban centers, international ports of entry, and large airports. They have a degree of self-reliance not found in urban areas.

Table 3. State-by-State Receipts, Cuts, Adds, and Claims for January 2019–December 2020

All 2020 and 2019 (statistic = sum)										
	Claims (2020)	**% Change**	**Shipment (2020)**	**% Change**	**Deliveries (2020)**	**% Change**	**Cuts (2020)**	**% Change**	**Adds (2020)**	**% Change**
Illinois	1.87E+05	90%	3.01E+07	13%	2.99E+07	13%	-1.67E+06	134%	4.59E+05	79%
Indiana	2.04E+05	-7%	2.17E+07	18%	2.15E+07	18%	-9.75E+05	160%	1.71E+06	169%
Iowa	2.22E+05	105%	2.06E+07	19%	2.04E+07	18%	-9.26E+05	26%	6.86E+05	87%
Michigan	1.82E+05	36%	3.24E+07	6%	3.23E+07	6%	-1.90E+06	162%	3.51E+05	156%
Minnesota	7.54E+04	0%	1.14E+07	42%	1.13E+07	43%	-6.34E+05	99%	1.48E+05	46%
Missouri	1.09E+05	15%	2.33E+07	16%	2.32E+07	16%	-1.87E+06	252%	9.09E+05	389%
North Dakota	1.80E+04	37%	1.47E+06	14%	1.45E+06	14%	-5.81E+04	155%	1.77E+04	100%
Ohio	1.41E+05	-5%	2.87E+07	5%	2.86E+07	5%	-1.64E+06	145%	2.46E+05	94%
Wisconsin	3.12E+05	15%	3.44E+07	14%	3.41E+07	14%	-1.42E+06	113%	1.13E+06	94%
Total	1.45E+06	25%	2.04E+08	14%	2.03E+08	13%	-1.11E+07	133%	5.65E+06	136%
Comparison of Period 1 (2020 and 2019) (statistic = sum)										
	Claims (2020)	**% Change**	**Shipment (2020)**	**% Change**	**Deliveries (2020)**	**% Change**	**Cuts (2020)**	**% Change**	**Adds (2020)**	**% Change**
Illinois	1.70E+04	-5%	8.34E+06	25%	8.32E+06	25%	-7.05E+05	261%	1.56E+05	29%
Indiana	3.51E+04	-29%	5.61E+06	27%	5.58E+06	27%	-3.91E+05	360%	5.77E+05	279%
Iowa	3.46E+04	53%	5.85E+06	32%	5.81E+06	32%	-3.86E+05	227%	2.79E+05	65%
Michigan	2.12E+04	-11%	8.13E+06	11%	8.11E+06	12%	-6.82E+05	194%	4.93E+04	6%
Minnesota	1.17E+04	-30%	3.45E+06	57%	3.44E+06	57%	-2.56E+05	106%	2.18E+04	-54%
Missouri	1.45E+04	-23%	8.81E+06	18%	8.79E+06	18%	-8.30E+05	315%	4.94E+05	405%
North Dakota	3.19E+03	-50%	3.69E+05	8%	3.66E+05	9%	-2.27E+04	238%	1.30E+03	-74%
Ohio	1.56E+04	-43%	7.29E+06	13%	7.27E+06	13%	-6.70E+05	341%	4.00E+04	31%
Wisconsin	1.15E+05	73%	9.49E+06	26%	9.37E+06	26%	-5.56E+05	201%	4.18E+05	157%
Total	2.68E+05	7%	5.73E+07	22%	5.71E+07	22%	-4.50E+06	247%	2.04E+06	144%

Table 3. Continued

Comparison of Period 2 (2020 and 2019) (statistic = sum)										
	Claims (2020)	**% Change**	**Shipment (2020)**	**% Change**	**Deliveries (2020)**	**% Change**	**Cuts (2020)**	**% Change**	**Adds (2020)**	**% Change**
Illinois	4.58E+04	110%	6.69E+06	14%	684E+06	14%	-2.63E+05	75%	8.13E+04	98%
Indiana	4.53E+04	-18%	4.96E+06	24%	4.92E+06	25%	-1.92E+05	197%	4.23E+05	281%
1owa	3.58E+04	55%	4.36E+06	20%	4.33E+06	20%	-1.54E+05	-63%	1.26E+05	102%
Michigan	4.97E+04	75%	7 20E+06	3%	7.15E+06	3%	-5.33E+05	330%	6.65E+04	313%
Minnesota	1.65E+04	68%	2.44E+06	41%	2.43E+06	41%	-1.23E+05	157%	2.87E+04	82%
Missouri	1.65E+04	-20%	4.43E+06	26%	4.41E+06	26%	-2.08E+05	147%	1.80E+05	810%
North Dakota	4.54E+03	361%	3.33E+05	18%	3.29E+05	17%	-1.27E+04	366%	3.77E+03	518%
Ohio	4.46E+04	6%	6.46E+06	4%	6.42E+06	4%	-3.03E+05	132%	4.64E+04	83%
Wisconsin	3.75E+04	-25%	7.77E+06	14%	7.73E+06	14%	-3.05E+05	160%	3.05E+05	147%
Total	2.96E+05	18%	4.48E+07	14%	4.45E+07	14%	-2.10E+06	85%	1.26E+06	203%

Comparison of Period 3 (2020 and 2019) (statistic = sum)										
	Claims (2020)	**% Change**	**Shipment (2020)**	**% Change**	**Deliveries (2020)**	**% Change**	**Cuts (2020)**	**% Change**	**Adds (2020)**	**% Change**
Illinois	1.24E+05	111%	1.49E+07	7%	1.48E+07	6%	-7.05E+05	90%	2.22E+05	137%
Indiana	1.24E+05	8%	1.11E+07	12%	1.10E+07	12%	-3.91E+05	74%	7.08E+05	91%
Iowa	1.52E+05	141%	1.04E+07	12%	1.02E+07	11%	-3.86E+05	92%	2.81E+05	107%
Michigan	1.11E+05	37%	1.71E+07	4%	1.70E+07	4%	-6.82E+05	85%	2.36E+05	215%
Minnesota	4.72E+04	-3%	5.51E+06	35%	5.46E+06	35%	-2.56E+05	73%	9.71E+04	158%
Missouri	7.75E+04	41%	1.00E+07	12%	9.96E+06	12%	-8.30E+05	236%	2.36E+05	245%
North Dakota	1.03E+04	78%	7.69E+05	16%	7.59E+05	16%	-2.27E+04	71%	1.26E+04	290%
Ohio	8.04E+04	3%	1.50E+07	1%	1,49E+07	1%	-6.07E+05	73%	1.60E+05	126%
Wisconsin	1.59E+05	4%	1.72E+07	9%	1.70E+07	9%	-5.56E+05	52%	4.05E+05	fi37%
Total	8.84E+05	35%	1.02E+08	9%	1.01E+08	9%	-4.50E*06	93%	2.36E+0E	105%

Methodologies

In the analysis, we generate descriptive measures for each product and product family. During the research, we tested several methods, including Naïve Bayes, K Nearest Neighbor Clustering with various distance measures, Support Vector Machine with and without One-Class unstructured separation, and Partition Trees. We found the best method was to use a $T2$ Hotelling Control Chart using $\alpha = 0.05$ to quantify when multivariate data showed either an outlier or if the process became out of control using ARL (average run length) metrics. Another reason for using the control chart methodology was the large weekly subsample size. Because there were 385 ordering locations, our ARL and upper control limit calculations were sufficient to detect process shifts. Hotelling control chart methodologies have precedence in literature for food SC monitoring and other nonmanufacturing applications (MacCarthy and Wasusri, 2002; Lim, Antony, and Albliwi, 2014; Juhászová, 2018). Traditional Statistical Process Control (SPC) assumes independence between observations (Montgomery and Mastrangelo, 1991). Appropriately, our five numeric features do not show autocorrelation in week-to-week data. The single exception was the claims feature in the second half of 2020 (Montgomery and Mastrangelo, 1991; Kandil, Hamed, and Mohamed, 2013; Mostajeran, Iranpanah, and Noorossana, 2018). Based on the low degree of autocorrelation, the upper control limits for determining outliers and out-of-control processes do not require Monte Carlo simulation or the use of residuals (Lim, Antony, and Albliwi, 2014; Vanhatalo and Kulahci, 2015). However, this study's aim is not to make more sensitive control charts but rather to identify substantial distribution shifts.

The Hotelling control chart is a multivariate extension of standard SPC procedures where k numeric features are assumed to be normally distributed. The observational vector **x** is a k-dimensional, **μ** is a vector of means for each k variables, and **Σ** is a square (k x k) covariance matrix. The Hotelling function is:

$$f(\boldsymbol{x}) = \frac{1}{(2\boldsymbol{\pi})^{\frac{p}{2}}\,|\boldsymbol{\Sigma}|^{\frac{1}{2}}}\; e^{-(x-\mu)\Sigma^{-1}\frac{\boldsymbol{x}-\mu}{2}} \tag{1}$$

To determine the T^2 statistic, we consider the sample covariance matrix **S** and the sample mean vector **μ** such that:

$$T^2 = (x-\bar{x})'\boldsymbol{S}^{-\mathbf{1}}(x-\bar{x}) \tag{2}$$

For small subsample sizes, the upper control limit for this chart is represented as:

$$UCL = \frac{(m-1)^2}{m} F_{\alpha,k/2,\frac{q-k-1}{2}} \tag{3}$$

where we use the F distribution, α as the confidence level, k as the number of features, m as the number of observations per period, n as the number of periods, and $q = \frac{2(n-1)^2}{3n-4}$. However, because m>38, the UCL calculation becomes $UCL = \chi^2_{\alpha,k}$ (Faraz and Moghadam, 2009a).

Using the T^2 chart, we separate an outlier from a process shift by considering the average run length (ARL) between points above UCL. ARL is a measure of whether an outlier indicates an aberration or a process shift. Because ARL_0 is the count of observations between outlier points, a small result indicates the lack of control where $(\mu \neq \mu_0)$. If this occurs after COVID-19, the inference is that the SC is not resilient and is exhibiting instability. Due to the large subgroup size in the data and relative independence in the samples, the ARL is computed directly rather than correcting for small sample sizes and autocorrelation (Faraz and Moghadam, 2009b).

In the case of the COVID-19 SC, ARL (approximates as $\frac{1}{\propto}$) is an indicator of process control. For this measure, the distance of the shift is d where $d^2 = (\mu - \mu_o)'\boldsymbol{\Sigma}^{-1}(\mu - \mu_o)$. An in-control process would be where d = 0, $\alpha = \Pr(T^2 > UCL | d = 0)$.

Although there is a significant chance that a genuine shift is not detected, as the α is set relatively high at 0.05, such that ARL should be less than 20. In cases where the quantitative analysis did not answer disruption and SC actions, researchers asked the company officials for more information.

We merged U.S. Census data and projections with company data to capture variables of interest, which included unemployment, education, income, rural influence, economic influence, and ethnic information scaled and normalized for analysis. Because U.S. Census estimates were only accurate for 2019, we merged 2020 poverty and unemployment estimates from the U.S. Bureau of Labor Statistics (BLS) to ensure the data represented the fluid nature of joblessness during the pandemic.

Our methodology for feature analysis was a random forest algorithm using bootstrap aggregation. This method is consistent with the disruption detection literature and robust given the sizes of our samples (Reif et al., 2006; Gharroudi, Elghazel, and Aussem, 2014; Ludwig, Feuerriegel, and Neumann, 2015; Lei et al., 2019; Alfaro-Cortés et al., 2020; Arora and Kaur, 2020). Although bootstrap forest is not the most powerful algorithm for regression and prediction, it is an efficient method for feature analysis given a large amount of data (Lei et al., 2019). The random forest algorithm uses bagging or bootstrap aggregation to analyze a dataset with $\boldsymbol{X}_p$ features and y_n targets B times with replacement, fitting trees for each iteration using a random sample of features (usually and in our methods √ p). This sampling of features allows us to compare the aggregated efficacy of each feature to predict the target t_b for each b = 1,…,B. This prediction is expressed as: $\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(\hat{y})$, where $\hat{y}$ are the predictions for test samples in that iteration.

We utilized established generalized linear modeling with K-Fold validation and partial least squares techniques to determine the effects of individual locations and generate *p*-values to check whether a factor was statistically significant. For the initial data processing, cleaning, exploration, and clustering parameter search, the research team used Python 3.7.3 (64 Bit) with NumPy and Pandas with an AMD Radeon RX 550 for parallel computation.

Findings and Discussion

Influential Factors Impacting Instability

In this analysis, we used bootstrapped random forest (B = 10000) with the count of out-of-control T^2 Hotelling points as the target (y) variable. We thought that demographic factors driving instability would change from 2019 to 2020 and between phases of the pandemic, which was only manifested in Period 1 2020, the initial surge, with unemployment moving from eighth most influential to first and the percent of adults with a high school diploma moving from third to sixth place. For all other examined periods, the drivers of instability remained consistent relative to each other (see Table 4). Although there are slight differences in feature contributions, it is evident that education rates and household financial indicators rates undoubtedly relate to instability in food SCs. In other words, this analysis indicates the stark reality that the ability to pay and education are always influential regardless of the level of uncertainty in a food SC.

Also, As COVID-19 policies drove the loss of jobs, unemployment's influence dominated SC variation for period 1. However, this dominance was short-lived, as the education factors returned to their previous influential level in periods 2 and 3.

We found no evidence of ethnic origin, racial groupings, age groups, migration (domestic and international), economics, education, and the rural nature of counties driving variability.

Our findings propose:

P1*:* Features contributing to supply chain instability remain stable during the majority of an extended global disruption. Other than the initial shock of immediate unemployment, the most important features include economic indicators (education level, percentages of poverty, and unemployment) with less influence from urban/rural composition and no effect from age groups, ethnicity, and migration.

Table 4. Feature Analysis of Economic, Educational, and Population by County Impacts to Instability by Period (Sums of Squares Vary Significantly between Periods Because of Varying Period Length) (n = 1000).

Period 1 (2019)

Feature	Contribution	SS
Percent of adults some college or associate's degree	0.1241	99.8227
Total population	0.1194	96.0235
Percent of adults with high school diploma	0.1117	89.8467
Percent of adults with no high school diploma	0.1043	83.8595
Percent of adults with bachelor's degree	0.1038	83.4813
Percent in poverty	0.0952	76.6084
Medan household income	0.0941	75.6857
Unemployment percentage	0.0889	71.5023
Rural code	0.0875	70.9431
Economic influence code	0.0711	57.1721

Period 1 (2020)

Feature	Contribution	SS
Unemployment percentage	0.2575	16.1532
Percent of adults some college or associate's degree	0.1141	86.8717
Percent of adults with no high school diploma	0.1041	79.2655
Total population	0.0915	69.9633
Percent in poverty	0.0831	63.2849
Percent of adults with high school diploma	0.0806	61.3499
Percent of adults with bachelor's degree	0.0761	57.9855
Median household income	0.0685	52.1542
Rural code	0.0631	48.0677
Economic influence code	0.0615	46.8294

Period 2 (2019)

Feature	Contribution	SS
Percent of adults some college or associate's degree	0.1356	218.8649
Percent of adults with no high school diploma	0.1366	210.8287
Total population	0.1095	176.7655
Percent of adults with high school diploma	0.1092	176.2579
Percent in poverty	0.0922	106.0629
Percent of adults with bachelor's degree	0.0959	154.7887
Median household income	0.0911	146.9921
Rural code	0.079	127.4788
Economic influence code	0.0752	121.2697
Unemployment percentage	0.0746	120.4429

Period 2 (2020)

Feature	Contribution	SS
Percent of adults some college or associate's degree	0.1361	172.8036
Percent of adults with no high school diploma	0.1255	159.3194
Percent of adults with high school diploma	0.1223	155.1894
Percent in poverty	0.113	143.4324
Percent of adults with bachelor's degree	0.1129	143.2837
Total population	0.1028	130.5094
Median household income	0.0936	118.7462
Unemployment percentage	0.074	93.9019
Economic influence code	0.0642	81.5361
Rural code	0.0556	70.5559

Table 4. Continued

Period 3 (2019)			Period 3 (2020)		
Feature	**Contribution**	**SS**	**Feature**	**Contribution**	**SS**
Percent of adults some college or associate's degree	0.1511	633.7475	Percent of adults some college or associate's degree	0.1403	577.8019
Percent of adults with high school diploma	0.133	588.0499	Percent of adults with no high school diploma	0.1295	533.6164
Percent of adults with bachelor's degree	0.1138	47.5535	Percent of adults with high school diploma	0.1215	500.3256
Total population	0.1112	466.4572	Percent in poverty	0.1185	488.1232
Percent of adults with no high school diploma	0.1028	431.2579	Total population	0.115	471.6895
Percent in poverty	0.0918	385.1189	Percent of adults with bachelor's degree	0.1057	435.5596
Median household income	0.087	364.8233	Median household income	0.0938	386.2434
Rural code	0.0785	329.339	Unemployment percentage	0.0619	254.0484
Unemployment percentage	0.069	289.5422	Rural code	0.0579	237.3302
Economic influence code	0.0619	259.6125	Economic influence code	0.0569	234.5131

As shown in Figures 2a and 2b, one of the significant findings of our analysis was that area population was correlated with the amount of demand growth. Quartiles 3 and 4 increased receipts by 15% and 14%, while quartiles 1 and 2 grew by 9% and 7%. The shipping adds in quartile 4 were 17 percentage points higher than other quartiles, suggesting that urban areas received disproportionate food supplies during periods of fluctuating demand (see Table 5a).

Conversations with the company's representative led us to theorize that it was not a deliberate action but was based on available transportation and distances between wholesale customers and DCs to reduce the risk of delayed delivery and ensure supplies' smooth flow. Therefore, we suggest that it is critical to keep in mind that:

P2: During prolonged global disruptions, food supply chains tend to prioritize meeting the pandemic-related demand shift of higher population areas first. This preference is primarily influenced by factors such as proximity to the distribution centers and the availability of transportation infrastructure.

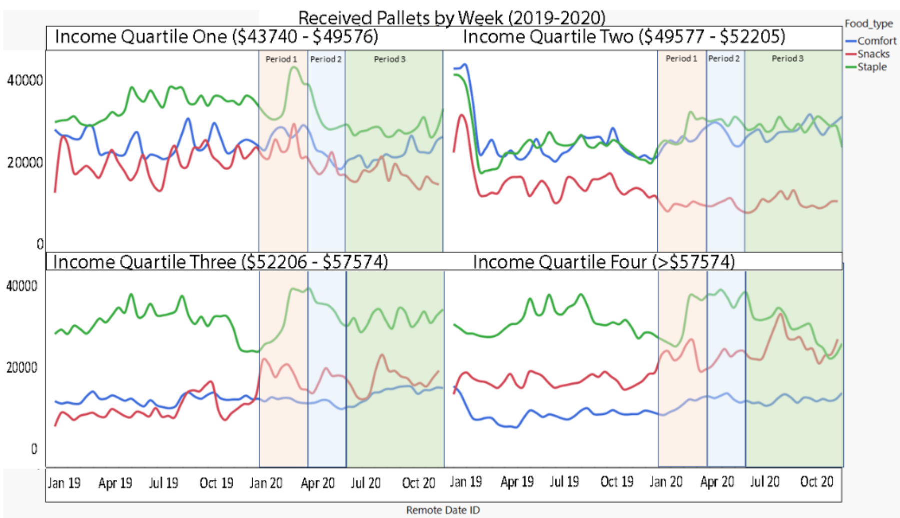

Figure 2a. Receipts Separated by Food Type

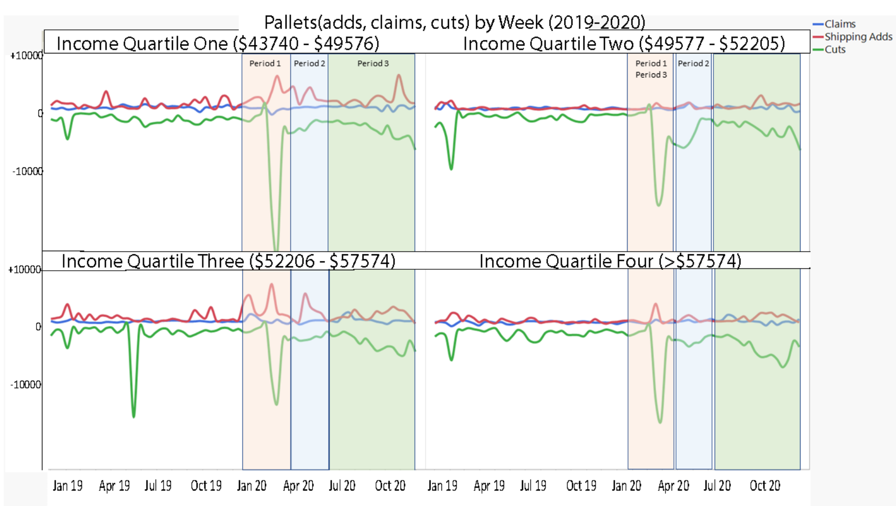

Figure 2b. Receipts Separated by Cuts, Adds, and Claims by County Population

Table 5a. Percent Changes in Cuts, Additions, and Receipts by County Median Income Quartiles

		2019 to 2020 Increases by Median Income Quartile, Period, and Food Type								
		Period 1			**Period 2**			**Period 3**		
Median Income Quartile (in USO)	**Food Type**	**Received % Change**	**Adds % Change**	**Cuts % Change**	**Received % Change**	**Adds % Change**	**Cuts % Change**	**Received % Change**	**Adds % Change**	**Cuts % Change**
One ($43,740–$49,576)	Comfort	28%	58%	82%	18%	74%	69%	31%	57%	62%
	Snacks	39%	79%	80%	23%	82%	74%	23%	65%	67%
	Staple	37%	50%	78%	15%	42%	41%	20%	77%	51%
Two ($49,577–$52,205)	Comfort	29%	28%	72%	15%	86%	75%	26%	64%	51%
	Snacks	6%	-144%	-33%	-48%	60%	28%	-15%	22%	63%
	Staple	41%	48%	78%	17%	59%	88%	24%	86%	68%
Three ($52,206–$57,574)	Comfort	29%	-62%	66%	15%	28%	62%	24%	77%	68%
	Snacks	55%	73%	63%	41%	82%	-153%	38%	48%	79%
	Staple	27%	33%	71%	3%	-96%	56%	12%	4%	1%
Four ($57,575–$61,492)	Comfort	40%	-11%	73%	31%	66%	64%	33%	67%	57%
	Snacks	41%	46%	51%	21%	73%	75%	39%	58%	79%
	Staple	29%	-82%	73%	12%	-29%	15%	7%	61%	12%

Another surprise in our analysis of product features was that cost was never prominent in any period, but food type was always a top contributing factor. Three food types were analyzed in our research. Snacks that are savory, ready-to-eat products; comfort foods that are typically sweeter and require more consumer preparation; and staples are foods that make up a dominant portion of the population's diet.

As presented in Figures 3a and 3b, for quartiles 1, 3, and 4 for median country income, demand for snacks increased by 28%, 44%, and 36%, respectively. Quartile 2 was the only income group for which staples were the food type, with the highest growth (27%) and decreased snack demand (-15%). For all income levels, snacks (30%) outgrew staples (20%) and comfort food (27%) (see Table 5b). We theorize that all income groups except quartile 2 enjoyed a higher availability of disposable income throughout 2020, which drove high demands for foods other than staples. It is probable that quartile 2 hosts a large portion of essential workers that stayed active and depended on their earned income; thus, they did not change their consumption habits. Similarly, looking at counties by population, only the lowest populated counties did not have increased demand for snacks, as evidenced by receipts (-2%), while all three higher populated quartiles increased demand for snacks by 15%, 28%, and 16%, respectively (see Figures 3a and 3b). Considering the unemployment support and pandemic relief payments from the government in addition to increased disposable income due to lack of dining out and entertainment options because of shelter-in-place and quarantine mandates, available funds were bolstered for families; therefore, we propose the following:

P3*:* Sufficient supplies of food staples and availability of disposable income support increased demand for nonessential food types during an extended global disruption.

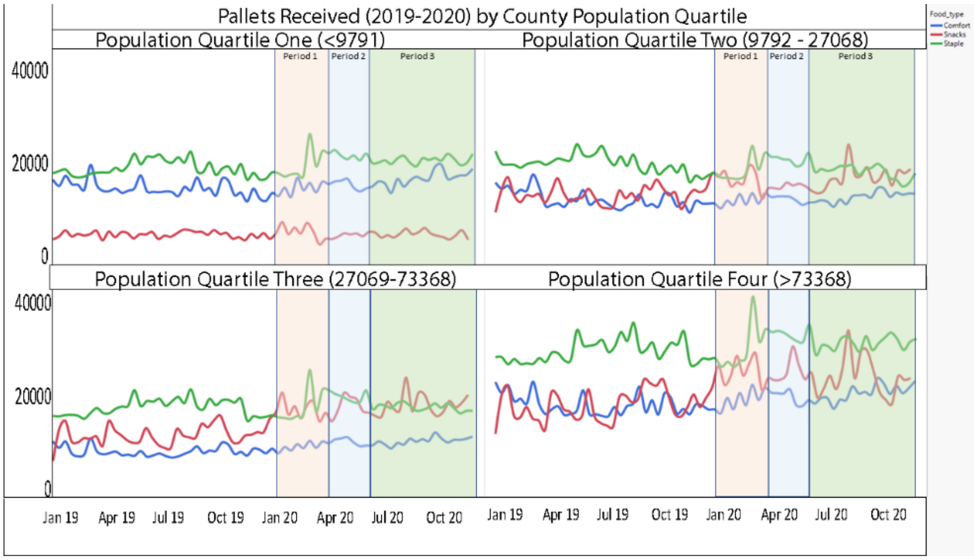

Figure 3a. Receipts Separated by Food Type

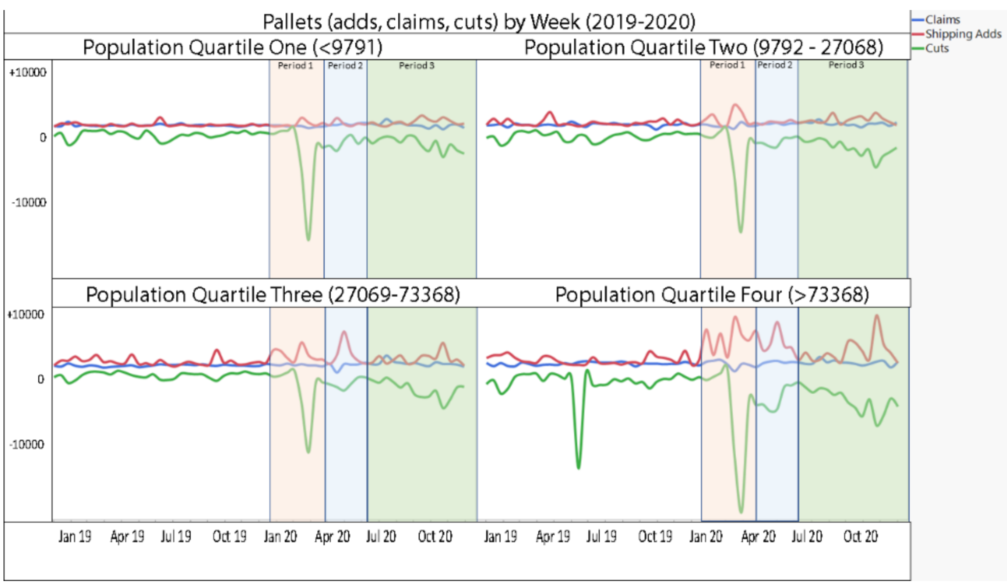

Figure 3b. Receipts Separated by Cuts, Adds, and Claims by County Median Income

Table 5b. Percent Changes in Cuts, Additions, and Receipts by County Median Population Quartiles

2019 to 2020 Increases by Median Income Quartile, Period, and Food Type										
		Period 1			Period 2			Period 3		
Median Population Quartile	Food Type	Received % Change	Adds % Change	Cuts % Change	Received % Change	Adds % Change	Cuts % Change	Received % Change	Adds % Change	Cuts % Change
One (0–9,791)	Comfort	12%	20%	76%	19%	69%	71%	14%	43%	47%
	Snacks	11%	-34%	52%	-2%	68%	65%	-8%	56%	67%
	Staple	18%	34%	77%	12%	9%	53%	0%	66%	24%
Two (9,792–27,068)	Comfort	0%	0%	76%	12%	74%	62%	11%	70%	56%
	Snacks	19%	68%	55%	10%	0%	62%	15%	20%	69%
	Staple	6%	49%	74%	5%	-15%	-4%	-6%	46%	18%
Three (27,069–73,368)	Comfort	6%	-88%	68%	23%	41%	68%	19%	63%	62%
	Snacks	28%	62%	53%	33%	86%	62%	25%	48%	79%
	Staple	7%	-40%	69%	7%	-159%	47%	0%	34%	17%
Four (73,369–5.2 million)	Comfort	12%	-18%	75%	21%	72%	70%	15%	69%	59%
	Snacks	28%	78%	55%	25%	90%	-91%	6%	52%	67%
	Staple	16%	10%	74%	16%	44%	80%	7%	62%	48%

Conclusions and Future Research

SCDs are common but most often very focused and of limited duration. They affect production, transportation, demand, supply, and different parts of a supply chain. Preparing and responding to SCDs can be the difference between a company's long or short-term success and failure. It is crucial to remember that consumer purchasing behavior is constantly changing, and there is no guarantee of predicting their response to various circumstances. However, understanding the drivers of SC stability from the point of view of the consumer's behavior in the food SC can have significant outcomes for businesses and communities worldwide.

The impact of COVID-19 on consumers' behavior is not comparable to any other previous calamity, as it caused massive changes to people's lives and the way they interact with the world around them.

During the COVID-19 pandemic, consumers worldwide have shown panic buying and stockpiling activity, resulting in empty shelves and causing disturbance in SCs and consumer behaviors (Taylor, 2021).

Images of empty shelves and news about people's stockpiling and panic buying shared by media and social media intensified fear and generated the perception of scarcity among people. Simultaneously, based on literature, the perception of the unavailability of products or services results in a perception of limited stocks and causes panic buying. In other words, the perception of scarcity created one.

Our study's results align with Kirk and Rifkin (2020), who evaluate consumer behavior during the COVID-19 pandemic by adapting the react-cope-adapt model. Accordingly, our initial observation reveals that consumers react to uncertainty at the onset of an epidemic by over-purchasing products, which boosts the pressure on the SC and imposes a disruption. Over time, although the consumers began to cope with the new environment by adopting new behaviors, the impaired SC struggled to return to regular operations due to the excessive damages created by the sudden growth in demand.

Also, the uncertain climate and perceived scarcity of resources imposed by COVID-19 undoubtedly contributed to anxiety and negative emotions that constitute an adverse change in consumer purchasing behavior and its effect on the SC compared to pre-COVID-19.

Our deep dive into data related to global and extended SCDs provides unique insight into food SC elements. As such, the findings articulated here offer broad insights to scholars and managers and opportunities for future research.

Contributions to the Theory

Because this paper is grounded in consumer behavior theory, it sharpens the understanding of how a global and extended food SCD affects demand variations. During the disaster, perceived scarcity, uncertainty about the future, and fear of losing control resulted in hoarding behavior, severely impacting the SC and contributing to SCD (Sim et al., 2020). Our study showed that the SCD length extends the uncertainty period, worsening demand fluctuations as SCD conditions change and other variability factors (shipping cuts, adds, and claims) are magnified as demand signals change. As a result, this high level of noise in the system increases the difficulty of returning the system to the pre-SCD stability position.

Also, the prominent demographic factors that account for SC variation are primarily economic in nature. Prior to the pandemic, education factors tied to economic power (high school diploma, college education, etc.) contributed the most to SC variation. This study contributes to the literature by showing that with the rise of the COVID-19, loss of jobs and unemployment were the dominant factors of SC variation. However, when the governmental policies and mandates relaxed and the economy started to reopen, the education factors returned to their previous influential level.

These remarkable results can be explained by the distribution of government funding and cost reduction policies that blunted what consumer behavior theory would typically indicate, which is that the external issue of unemployment would become the driving factor during a crisis with extended unemployment. In other words, the unemployment factor resulted in an initial change in features until the modifying elements were fully in place. So, expected crisis dynamics were blunted or changed when governments and employers acted in ways that changed the features that are traditionally associated with crisis consumption.

Although based on the dynamic capability theory, while the company grew its distribution to communities of all population sizes, rural areas received less product. It was noteworthy that the increased demand associated with the pandemic drove perceived scarcity and focused the SC response on increasing the supply to cities, the highest populated areas. High-population areas have more media presence and often are close to DCs. The combination of closer proximity and enhanced awareness of scarcity influence SC's efforts to meet these visible needs.

Furthermore, the results of our study revealed a unique phenomenon unattended in the marketing literature's consumer behavior theory in that nonessential food consumption increased during the pandemic. In other words, even with the global, extended nature of the COVID-19 pandemic, food insecurity was not visible in this company's SC. Demand for staples grew, but staples growth was dominated by comfort food and snacks, which experienced 7 and 10 percentage points more growth. Government payments to families and the ability of individuals to work remotely maintained a level of income that met basic needs with staples and drove higher demand for snacks and comfort foods. This demand may have been a response to the boredom of lockdowns, which is in line with the result of Porter et al. (2022), as they report a significant increase in snack and junk food consumption during COVID-19 around the world.

Contributions to Practice

This study explains the variation in the demand for food products based on the demographic factors that affect consumers' purchasing behavior. Our analysis could assist businesses in better understanding consumers' decision-making processes during an extended global crisis to transform and progress with the times. Our research points to the following managerial insights to better address extended global SCDs for food SCs. First, widespread humanitarian SCDs create fear and concern for food security, leading to changes in consumer behavior and increased demand for specific products. So, based on their capabilities, companies need to work to meet immediate demand, assess their network design, and examine the results of temporary fixes to understand what is driving instability.

Finally, our study is notable in that considering the role of demographic factors on SC instability assists policy makers and managers in understanding customers' purchasing behavior during an extended crisis and developing appropriate strategies to maintain a stable SC. It reveals that consumers will not respond in the same way under the same critical situation, resulting in unexpected demand patterns during SCD. The company examined in this study experienced the highest demand growth in snacks and comfort food, revealing that companies should be aware that they may meet the basic survival needs of consumers (in this case with staples) but experience a higher demand for nonessentials that may be important for other humanitarian reasons, like morale or mental health.

Limitations and Future Research

The results of this research will have some generalizability for companies that provide essential products for affected populations during SCDs. Since our analysis is related to the food supply chain, some of the propositions may not apply entirely to firms in other industries. Moreover, companies with less shelf life or damage issues may have different dynamics and may need to have additional analyses.

Although our data are from an international food manufacturer that produces and distributes in North American countries, our analysis was limited to the data related to the wholesale-to-wholesale orders and shipments for the United States Midwest. We tried to characterize the immense amount of this data and uncover some general findings related to long-term SCDs. However, much more can be explored with this data and this company. In future research, we expect to expand our Midwest study to the entire United States. Additionally, there are other SC dynamics that we could not cover in this paper. Future research should examine pandemic factors driving bullwhip effects, how to better interpret distribution data (adds, cuts, claims, etc.) during a supply chain disruption, and the dynamic nature of distribution/transportation networks in response to disturbances.

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