The role of forecasting in preventing supply chain disruptions during the COVID-19 pandemic: a distributor-retailer perspective

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Abstract

Strengthen the resilience of supply chains was observed to be critical issue by firms to confront disruptions triggered by unprecedented demand and severe disasters. However, the extraordinarily challenging disruptions of COVID-19 pandemic, unlike any disasters seen in recent times. This study aims to provide a practical solution to supply chain (SC) disruptions by estimating the best forecasting models for demand fluctuations in the context of food and beverages. A method is proposed to predict SC disruptions and enhance SC resilience. Double exponential smoothing (DES) and the ARIMA model are adopted as forecasting approaches to estimate demand and optimum inventory quantities during three different periods of disruption associated with the COVID-19 outbreak. A downstream SC involving 2 distributors and 56 retailers is considered to elaborate inventory measurements (optimal inventory levels and total costs). The results demonstrate that distributors can reduce costs by dispensing with some retailers, particularly those who order low quantities and thus incur unjustified expenses. Furthermore, high accuracy is obtained, with minimal differences between the real data and the model's forecast. Existing research has largely ignored supply disruptions in the distributor-retailer relationship. This study provides distributors and SC managers important knowledge on SC disruptions and identifies appropriate forecasting methods to increase SC resilience. It also provides distributors and other SC managers unprecedented insights on tackling crises of stability like COVID-19.

Keywords Forecasting · ARIMA model · COVID-19 pandemic · Supply chain resilience · Time series

1 Introduction

The effects of the COVID-19 pandemic have not only brought huge challenges for the health sector but also increased demand volatility and threatened the resilience of supply chains (SCs), especially in the food sector (Aljanabi 2021; Chowdhury et al. 2021; Chauhan et al. 2022b). As a result, food prices have increased in many countries (Prentice et al. 2020; Hobbs 2021; Thilmany et al. 2021), and people around the world have engaged in periodic stockpiling to cope with the threat (Aljanabi 2021). Furthermore, COVID-19-related restrictions have made providing essential goods (e.g., food and medicine) a significant logistical issue for both distributors and retailers. Distributors and retailers have been forced to adjust their marketing activities from maximizing profits to reducing costs (World Bank 2021), particularly in markets that are highly dependent on imported goods rather than local production (Barua 2020), such as Iraq (Noor and Aljanabi 2016). The United Nations Iraq report indicated a steep decline in local production in food-related industries of 61% (UNI 2020), which coincided with the complete closure of the country's borders and the enforcement of strict measures to restrain the spread of COVID-19. Finding alternative sources of certain food items has become a challenge for distributors (WFP 2020), and international reports have recommended that Iraqi agencies and distributors evaluate demand fluctuations in order to assess the impact and adjust their response accordingly (UNI 2020).

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The negative impact of the COVID-19 outbreak has attracted increasing attention from researchers in the fields of marketing and SCs. Nonetheless, the implications of the COVID-19 pandemic for the distributer-retailer relationship have been largely unexamined. Chowdhury et al. (2021) noted that related research has focused on the effects of past epidemics, like Ebola and malaria, on food SCs, with very few analyses of the response plans formulated by SC managers during health crises. Sharma et al. (2020) argued that the literature addressing SC resilience in different phases of the COVID-19 pandemic remains limited. Studies of the impact of the COVID-19 pandemic on SC activities are particularly warranted in the context of food distribution (Singh et al. 2021; Chauhan et al. 2022a).

Unlike previous diseases, COVID-19 has severely impacted all SC members and ties (Chauhan and Singh 2021; Chowdhury et al. 2021) and caused equally drastic disruptions upstream and downstream simultaneously (Ivanov and Das 2020; Nikolopoulos et al. 2021). A recent study concluded that downstream operations have a greater impact on SC performance than upstream operations (Olivares-Aguila and ElMaraghy 2021). Upstream SC disruptions mainly pertain to inventory optimization, lot sizing, and supplier selection (Chowdhury et al. 2021), whereas distributer-retailer coordination and demand scheduling are critical for reducing downstream disruptions and enhancing SC resilience (Swierczek 2020; Zhao et al. 2020).

Although the COVID-19 pandemic is primarily a public health crisis, it brought an unexpected surge in the demand-side of essential goods due to panic buying and stockpiling behaviors (Prentice et al. 2020). Demand planning offers SC managers a clear pathway to establish forecasts that support performance and increase SC resilience (Chauhan and Singh 2017; Swierczek 2020). More specifically, demand planning and downstream integration decrease the probability of demand disruptions, in turn leading to greater SC resilience to unexpected demand (Aljanabi and Ghafour 2020). Hence, during the pandemic, forecasting has become a fundamental tool for effective decision-making as demand disruptions due to lockdowns and disease severity continue (Nikolopoulos et al. 2021).

By considering demand volatility before, during and after the peak of the COVID-19 pandemic, this study aims to address the following questions:

RQ1: What are the best models for forecasting demand volatility in terms of the trade-off between high customer value and required quantity in the context of food and beverages?

RQ2: How can different levels of SC resilience be achieved according to the urgency of the ordered quantity or COVID-19 pandemic severity?

RQ3: What performance measures should distributors use to select the optimal forecasting model?

The main objectives of this study are to elaborate a forecasting model that optimizes the quantity of demand for food and beverages before, during and after the peak of the COVID-19 pandemic and to predict future potential SC disruptions. In addition, this study aims to explain how distributors operate during this crisis to increases the flexibility of SCs to confront demand variability and prevent similar situations in the future.

Prior research has identified the most common barriers in SC management. However, some studies did not reflected the viewpoints of supplier managers and did not provide empirical evidence on SC resilience (Pereira et al. 2021). While others did not empirically test how to create value through resilience capabilities (Ivanov 2021). Thus, the major contributions of this study are as follows. First, this study addresses the gap in the demand forecasting literature related to the COVID-19 outbreak and the poor resilience of SCs to the associated unexpected demand. Second, it shifts the focus of studies on SC disruptions from detection methods to response behaviors in order to increase the resilience of businesses to unexpected demand. Third, it strengthens the understanding of distributer-retailer coordination, which has not received much attention. Finally, the robust applied methodology, which includes the collection of data from different periods of the pandemic, enhances the study's applicability to similar crises.

The remainder of this study is structured as follows. Section 2 reviews the theoretical background. Section 3 presents the problem description. The model and research methodology are described in Sects. 4 and 5, respectively. Section 6 presents the data analysis and results. Section 7 provides a discussion. Section 8 highlights the managerial implications. The conclusion is provided in Sect. 9. Finally, limitations and future research are discussed in Sect. 10.

2 Theoretical background

2.1 Supply chain disruptions during the COVID-19 pandemic

In addition to bringing considerable human suffering, the COVID-19 pandemic has laid bare the diverse failures of SCs to prepare for and respond to demand disruptions (Lotfi and Larmour 2021; Thilmany et al. 2021). The severity of the COVID-19 pandemic and its repercussions for SC disruption have challenged our understanding of SC resilience built on the abundant SC resilience literature (Nikolopoulos et al. 2021). SCs have grown longer and more complicated due to an increasing reliance on external sources, turbulent

global conditions, and globalization, making markets more vulnerable to severe supply shortages and contributing to the failure of SCs to respond to pandemic disruptions (Zheng et al. 2020; Sharma et al. 2021). Although inventory policies can resolve temporary supply disruptions, immediate supply disruptions resulting from lockdowns and curfews cannot be offset (OECD 2020). Therefore, improvements in the adaptive capability of SCs to face unexpected conditions are necessary to help firms restore confidence and mitigate demand disruptions during the pandemic (Lotfi and Larmour 2021).

When the duration of supply disruption is unknown and potential solutions are unclear (Ghafour 2018; Aljanabi 2021; Boehme et al. 2021), firms seeking resilient SCs should focus on situational responses to dynamic market changes rather than proactive procedures (Ponomarov and Holcomb 2009; Ivanov and Das 2020). The recent SC literature suggests that maintaining collaborative partner relationships to estimate and manage SC risks is indispensable not only to strengthen SC activities (e.g., inventory control, demand and supply management) but also to develop the resilience required to handle disruptions during and after COVID-19 in a competitive manner (Cao et al. 2021; Lotfi and Larmour 2021; Sharma et al. 2021; Zhang et al. 2021). SC partners can pursue collaboration by sharing information, which plays a fundamental role in overall SC performance, reducing communication barriers, and providing near-optimal solutions for SC disruptions (Ponomarov and Holcomb 2009; Ghafour et al. 2017; Aljanabi 2018; Tliche et al. 2019; Cao et al. 2021; Swierczek 2020) noted that sharing information on real demand enables the identification of disruptions and increases the flexibility of SCs to confront demand variability. Such knowledge management via sharing critical information can also be a supportive analysis tool in dealing with scenario planning and rectifying the impacts of COVID-19 disruptions (Chowdhury et al. 2021; Sharma et al. 2021), particularly for downstream operations, which have a greater impact on SC performance than upstream operations (Olivares-Aguila and ElMaraghy 2021).

Despite the potential advantages of adopting a collaborative approach via information sharing, the lack of analytical tools that can facilitate the prediction of future demand and potential disruptions remains one of the most common barriers in SC management (Zhang et al. 2021). Forecasting is an important tool that decision-makers can utilize to increase SC resilience to potential demand disruptions (Ivanov and Dolgui 2021; Nikolopoulos et al. 2021).

2.2 The necessity of forecasting for supply chain resilience analysis

Supply managers seeking to rectify demand shortages are interested in identifying potential disruption scenarios to enhance decision-making and to determine what actions are required for recovery (Ghafour 2017; Ivanov and Dolgui 2021). The breakdown of SCs and the wide impact of COVID-19 have provided clear evidence of the urgent need to develop resilient SCs that can employ robust strategies to accommodate external disruptions (Ivanov and Das 2020; Chowdhury et al. 2021). The demand for resilient SCs is emphasized by the continued popular discourse on the weakness of SCs and their failure in the face of the pandemic (Hobbs 2021).

As a dynamic process, SC resilience has been defined as "*The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.*" (Ponomarov and Holcomb 2009, p. 131). In the recent literature, SC resilience has emerged as a fundamental issue in embracing change and enduring global shocks emerging from the pandemic (Olivares-Aguila and ElMaraghy 2021; Pereira et al. 2021; Schleper et al. 2021). However, few studies have adopted a quantitative approach to identify potential opportunities to increase SC resilience by studying SCs as a single construct, and there has been little focus on the ability of decision-makers at the organizational level to predict the potential disruptions arising from the COVID-19 pandemic (Ivanov and Das 2020; Nikolopoulos et al. 2021; Singh et al. 2021). The majority of studies have employed a qualitative approach to evaluate SC resilience problems (Chowdhury et al. 2021; Hobbs 2021; Ivanov and Dolgui 2021). Table 1 summarizes previous studies of SC resilience during the COVID-19 pandemic in terms of purpose, methodology, and limitations.

To bridge this gap in the literature, this study utilizes two different forecasting methods, namely double exponential smoothing (DES) and the ARIMA model, to address different demand issues before, during and after the peak of the COVID-19 pandemic.

2.2.1 Double exponential smoothing

DES is a powerful forecasting method that can be utilized to analyze data with a systematic trend (Holt 2004). DES applies a smoothing level and a trend at each period using two weights called smoothing parameters for the purpose of updating the elements at each period. To extract the DES, the following equation is employed (Moiseev 2021):

Table 1 Summary of previous studies of SC resilience during the COVID-19 pandemic

No.	Author name (Year)	Purpose	Method	Limitations
1.	Boehme et al. (2021)	To examine the response of personal protective equipment companies to a SC crisis	Longitudinal study	The applied methodology did not empirically test the propositions.
2.	Golan et al. (2020)	To review the SC resilience literature	Systematic literature review	The applied methodology did not provide empirical evidence.
3.	Hobbs (2021)	To discuss the agrifood SC and unique features of this SC that need to be considered when evaluating resilience	Qualitative study	The study did not provide empirical evidence for agrifood SC resilience.
4.	Hoek (2020)	To suggest a pathway for research to develop more resilient SCs	Impact pathway analysis	The applied methodology did not empirically test the study suggestions.
5.	Ivanov (2021)	To provide a framework for efficient SC resilience and to highlight how to create value through resilience capabilities	Qualitative study	The study did not empirically test how to create value through resilience capabilities.
6.	Ivanov and Das (2020)	To model the effect of COVID-19 on global SCs and to analyze supply risk-mitigation measures	Scenario analysis	Cross-country scenarios may not be feasible at the organizational level.
7.	Ivanov and Dolgui (2021)	To explore the conditions of the design and implementation of the digital SC twins model.	Conceptual research	The applied methodology did not empirically test the suggested principles.
8.	Lotfi and Larmour (2021)	To assess the effects of horizontal and vertical SC collaboration on SC resilience	Thematic analysis	The applied methodology did not empirically test the propositions.
9.	Nikolopoulos et al. (2021)	To provide predictive analytics for excess demand for products and services	Hybrid forecasting method	Cross-country collection of data may not be feasible at the organizational level.
10.	Olivares-Aguila and ElMaraghy (2021)	To introduce a system dynamics framework to examine SC disruptions	System dynamics	The applied method is not suitable for optimization and is very complex, with modelling of many variables in actual situations.
11.	Pereira et al. (2021)	To investigate the impact of COVID-19 on SC sustainability learning	Case study	The gathered data reflected the viewpoints of supplier managers and did not provide empirical evidence on SC resilience.
12.	Schleper et al. (2021)	To provide a structured discussion of the impacts of the COVID-19 pandemic on retail	Qualitative study	The study did not provide empirical evidence on the impact of COVID-19 on demand and optimal inventory levels.
13.	Sharma et al. (2021)	To explore post-pandemic priorities for retail SCs	Integrated full consistency model and best–worst method	The assessment method based on experts' opinions may be biased and does not forecast future demand.
14.	Singh et al.(2021)	To identify disruptions in the food SC and to highlight the importance of a resilient SC during COVID-19	Scenario analysis	The study focused on a delivery system to reach out to customers residing in a high-rise condominium.
15.	Thilmany et al. (2021)	To highlight drivers of different local responses to food SC disruptions during COVID-19	Qualitative study	The study did not provide empirical evidence on SC resilience drivers.
16.	Zhang et al. (2021)	To identify the most SC-resilient company	Hybrid multi-criteria model	The study did not forecast the impact of COVID-19 on demand and optimal inventory levels.

$$S_t = \alpha Y_t + (1 - \alpha)(S_{t-1} + T_{t-1}) \qquad (1)$$

$$T_t = \gamma\left[L_t - L_{t-1}\right] + (1 - \gamma)\,T_{t-1} \qquad (2)$$

$$\widehat{Y}_t = S_{t-1} + T_{t-1} \qquad (3)$$

where,

S_t: Level at time t.

α: Weight for the level

T_t: Trend at time t.

γ: Weight for the trend

Y_t: Data value at time t.

$\widehat{Y}_t$: Forecasted value at time t.

The current value of the series is used to estimate its smoothed value replacement in DES. There are different ways to determine the initial value of T_1:

$$T_1 = Y_2 - Y_1 \qquad (4)$$

$$T_1 = \frac{\left[(Y_2 - Y_1) + (Y_3 - Y_2) + (Y_4 - Y_3)\right]}{3} \qquad (5)$$

$$T_1 = (Y_3 - Y_1)\,(n - 1) \qquad (6)$$

The mean absolute deviation (MAD) can be used to measure the accuracy of tailored time-series values. MAD expresses accuracy in the same units used to estimate the amount of error (Leung et al. 2009). The formula of MAD is given by the following equation:

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \widehat{Y}_t\right| \qquad (7)$$

where n is the number of observations.

2.2.2 ARIMA Model

The ARIMA model is a well-known forecasting model in economics and finance that was first introduced by Box and Jenkins (1976). The ARIMA model is used to estimate the correlations in time-series data to build a forecasting model. The "AR" in ARIMA stands for "autoregressive". Autoregression is introduced by p in the model, which indicates the number of lags of Y to be used as a forecaster. Yt depends only on the weighted sum of the products of the previous observations (Y_{t-1}, Y_{t-2},…), which represents the pure AR

model (Satrio et al. 2021). A practical demonstration of an autoregressive model of order p is shown in the following equation:

$$Y_t = C + \varnothing_1 Y_{t-1} + \varnothing_2 Y_{t-2} + ... + \varnothing_p Y_{t-p} + \epsilon_t \qquad (8)$$

where $\varnothing_1, ..., \varnothing_p$ are the corresponding coefficients of observations Y_t to be estimated in past periods and ϵ_t is a white noise term. The "MA" in ARIMA refers to "moving average", which is introduced by q in the model. Unlike the AR model, which uses previous observations, the MA model depends only on previous forecast errors. A practical demonstration of an MA model of order q is shown in the following equation (Swaraj et al. 2021):

$$Y_t = C + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + ... + \theta_q \epsilon_{t-q} \qquad (9)$$

where $\theta_1, ..., \theta_q$ are the estimated coefficients that give the stationarity of the time series. The "I" in ARIMA corresponds to "integrated" and is introduced by d in the model. When the time series is differenced at least once to create a stationary time series and pooled with the AR and MA models, a non-seasonal ARIMA model is obtained. In this situation, differencing is the reverse of integration. The equation for ARIMA can be represented as follows:

$$Y_t^{/} = C + \varnothing_1 Y_{t-1}^{/} + ... + \varnothing_P Y_{t-p}^{/} + \theta_1 \epsilon_{t-1} + ... + \theta_q \epsilon_{t-q} + \epsilon_t \qquad (10)$$

where $Y_t^{/}$ indicates a set of differences that have been compared several times and the right side of the formula includes both lagged observations from the AR model and lagged errors from the MA model (Josephraj et al. 2020).

3 Problem description

Prior to the COVID-19 pandemic, studies focused on food SC resilience examined specific disruption scenarios, such as supplier selection (Chowdhury et al. 2021). Most of these studies were qualitative studies (Currie et al. 2020; Golan et al. 2020; Rowan and Laffey 2020; Chowdhury et al. 2021) or made limited attempts to consider how the effects of the distributer-retailer relationship and demand scheduling might reduce downstream disruptions and enhance SC resilience (Swierczek 2020; Zhao et al. 2020; Deaton and Deaton 2021). During the COVID-19 pandemic, marketers have faced severe shortages of food products due to abnormal demand (Aljanabi 2021). Many mitigation strategies have been suggested in the literature to enhance SC resilience and promote the ability of SCs to match supply with demand.
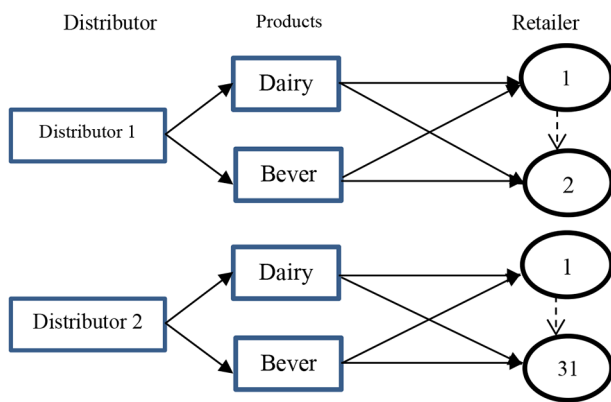
Fig. 1 Distributor-retailer channels

Examples include increasing production rates in line with expected demand (Mehrotra et al. 2020) and integrating online shopping into purchasing processes to improve logistics and align SC activities with imposed measures (Rowan and Laffey 2020; Aljanabi 2021; Deaton and Deaton 2021). However, remote work and social distancing measures have reduced the production capacity of many businesses around the world (Leite et al. 2020). To cope with imposed preventive measures, SCs need to adopt more flexible strategies that enable them to build robust partnerships and increase their resilience to external disruptions (Ivanov and Das 2020; Chowdhury et al. 2021).

To increase SC resilience and build more robust partnerships, this study uses a forecasting method to estimate demand and optimum inventory levels during three different periods of the COVID-19 outbreak. In addition, to address uncertain consumer behaviors such as panic buying and stockpiling, which may affect both demand and lead time and increase distributor-retailer disruptions, the ARIMA model is used to analyze the impact of the three different periods of the COVID-19 pandemic on demand.

4 Model description

This study considers two distributors who deal with a specific number of retailers in the food and beverages sector before, during and after the peak of the COVID-19 pandemic, as shown in Fig. 1. Accordingly, this study aims to extract the optimal order quantity and its cost for each retailer, in addition to establishing the best model for forecasting demand volatility that will achieve SC resilience according to the urgency of the order or COVID-19 pandemic severity.

The following assumptions are made in formulating the model:

- The order lead time between the distributors and retailers is fixed to one week to equip retailers with both products.
- Shortages are not allowed.
- Only the holding cost and setup cost are considered.
- The total cost for the first distributor is $4750/month, including the holding cost and setup cost.
- The total cost for the second distributor is $5250/month, including the holding cost and setup cost.
- Demand over each period for each retailer is continuous and with a probability rate.
- Demands are probabilistic with a probability distribution function in the three different periods: before, during and after the peak of the COVID-19 pandemic.
- The order quantity and cost are not identical among retailers.
- The inventory control includes two products: dairy foods and beverages.

5 Research methodology

This study uses two different forecasting models to estimate the quantity of demand before, during and after the peak of the COVID-19 pandemic. DES is utilized to optimize the order quantity and extract the expected total cost for each retailer in the research sample, which enables distributors to choose the most optimal retailers and dispense with the other retailers in light of costs and demand quantities (Nikolopoulos et al. 2021; Shahed et al. 2021). Then, the ARIMA model is applied as a forecasting algorithm to predict the potential disruptions in the chain as a whole, eliminate disruptions that occur in the chain, and attain the best expectations for the items considered in the study (Rajak et al. 2021; Song et al. 2021).

5.1 Data collection

Demand data were obtained from two distributors operating in the city of Sulaimanyha in the Kurdistan region of Iraq. The demand data covered three periods: before the COVID-19 pandemic (11 January 2020 to 10 April 2020; 14 weeks), during the lockdown period (17 April 2020 to 7 December 2020; 34 weeks), and after the peak of the COVID-19 pandemic (8 December 2020 to 31 July 2021; 39 weeks). This study focused on two main products: dairy foods and beverages. The first distributor supplied 25 retailers, and the second supplied 31 retailers. The required quantity of demand was estimated in dozens per week.

5.2 Optimizing order quantity and cost

The optimal order quantity is the amount that minimizes the whole inventory cost in terms of the holding cost and setup cost. In this regard, Blackburn and Scudder (2009) suggested a cost function to minimize the cost value in the inventory model as shown in the following equation:

$$\begin{pmatrix} Total \\ inventory \\ cost.TC \end{pmatrix} = \begin{pmatrix} Purchasing \\ cost, c \end{pmatrix} + \begin{pmatrix} Holding \\ cost, h \end{pmatrix} + \begin{pmatrix} Setup \\ cost, k \end{pmatrix} + \begin{pmatrix} Shortage \\ cost, p \end{pmatrix}$$

According to the model assumptions, shortage cost is not allowed in this study. Furthermore, the purchase cost can be eliminated from the following equation as suggested by Taha (2017):

$$\begin{pmatrix} Total \\ inventory \\ cost.TC \end{pmatrix} = \begin{pmatrix} Holding \\ cost, h \end{pmatrix} + \begin{pmatrix} Setup \\ cost, k \end{pmatrix}$$

This study considers two distributors and 56 retailers, comprising 25 and 31 retailers for the first and second distributors, respectively. The holding cost for each retailer can be represented as

$$h_i, i = 1, 2, ..., n$$

. By contrast, the setup cost is constant for each distributor and is independent of the order quantity. In addition, the demand lead time D_L for each retailer is independent of the values for the other retailers. Thus, the demand lead time can be represented as $D_{Li}, i = 1, 2, ..., n$. Similarly, the total inventory cost TC and the order quantity q extracted for each retailer differ depending on h_i and D_{Li}. Thus, the total inventory cost and the order quantity can be represented as $TC_i \& q_i$, respectively. However, $\frac{q}{2}$ is the average inventory level during a cycle, and the corresponding length of the cycle is $\frac{q}{D_L}$ (Hillier and Lieberman 2010). Therefore:

$$holding \, cost, h_i / cycle = \frac{h_i q_i^2}{2D_{Li}} \quad (11)$$

where D_{Li} is the demand lead time established from Eq. (3) in the forecasting method (DES) for one period ahead (one week).

Therefore,

$$TC_i \, per \, cycle = K + cq_i + \frac{h_i q_i^2}{2D_{Li}} \quad (12)$$

The total cost per unit time is:

$$TC_i = \frac{K + cq_i + \frac{h_i q_i^2}{2D_{Li}}}{\frac{q_i}{D_{Li}}} = \frac{D_{Li}k}{q_i} + D_{Li}c + \frac{h_i q_i}{2} \quad (13)$$

For this, we derive the first derivative

$$\frac{dTC_i}{dq_i} = -\frac{kD_{Li}}{q_i^2} + \frac{h_i}{2} \quad (14)$$

By setting Eq. (14) equal to zero, we obtain

$$q_i^* = \sqrt{\frac{2kD_{Li}}{h_i}}, i = 1, 2, ..., n \quad (15)$$

Equation (15) represents the optimal order quantity. The total cost per unit time can be obtained by substituting Eq. (15) into Eq. (13) as follows:

$$TC_i = \sqrt{2?Kh_iD_{Li}}, i = 1, 2, ..., n \quad (16)$$

Given that the supply disruptions, especially in the food and beverage sector, resulting from lockdowns and curfews rather than inventory shortage or poor inventory control, so that shortage cost can be excluded in the model (Woo et al. 2021; Ghafour 2022).

5.3 Forecasting the excess demand before, during and after the peak of COVID-19

The demand for food and beverages typically follows a mostly stable pattern, particularly under normal conditions. However, during the pandemic, customers' buying behavior became more volatile due to SC disruptions and episodes of panic buying (Chandon and Wansink 2006; Nikolopoulos et al. 2021). Here, the ARIMA model (p, d, q) is applied to improve forecast accuracy under pandemic conditions. To select the appropriate model for the series in question and to verify the goodness of fit of the ARIMA model, the Akaike Information Criterion (AIC) is applied (Swaraj et al. 2021). The grid optimization method is used to elaborate the ARIMA model with the lowest AIC value among all possible combinations of parameters at a given interval (Dave et al. 2021). Seasonal analysis is used to test for seasonality in the dataset before applying the ARIMA model. The *AIC* for a fitted ARIMA time series of a specific length is defined as (Portet 2020):

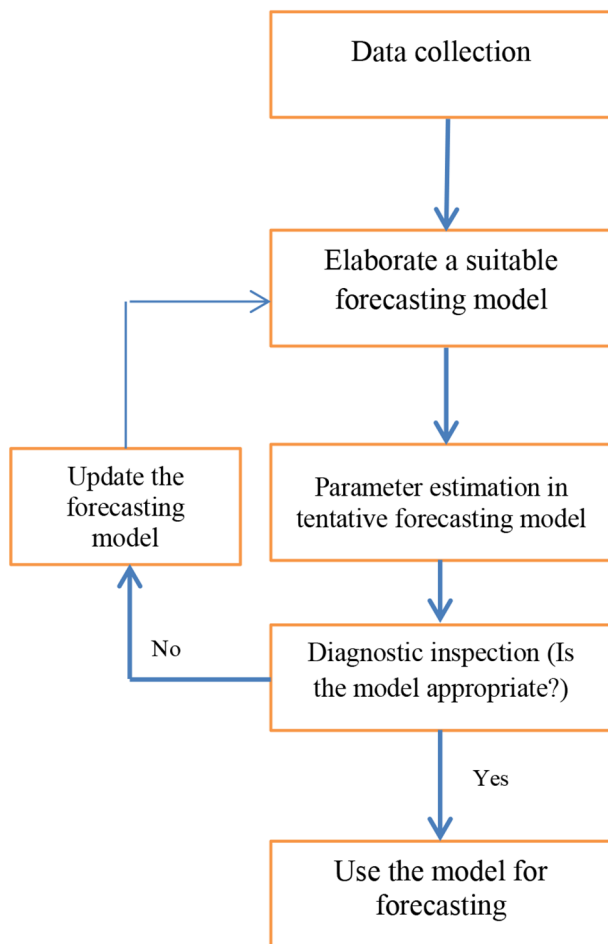$$AIC = \ln\left(\hat{\sigma}_{p,q}^2\right) + \frac{2(p+q)}{n} \quad (17)$$

Fig. 2 Forecasting procedures

Table 2 Total cost extraction

Distributors	Remaining retailers	Before dispenses	After dispenses
First	16 of 25	$ 57,576	$53,507
Second	21 of 31	$211,234	$202,343

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| Y_t - \widehat{Y}_t \right| \qquad (20)$$

6 Data analysis and results

6.1 Optimal order quantity q^* and its total cost TC

To obtain the optimal order quantity q^* and the total cost function TC from Eqs. (15) & (16), we first need to extract the demand lead time D_L from Eq. (3) for the *DES* model for one period ahead (one week). The first forecasted value at time t is extracted from Eq. (4) (Moiseev 2021), and all other elements are as assumed previously (e.g., K, h).

There is clearly an impact of pandemic severity on the data fluctuations: before the pandemic, the fluctuations in the data have a stationary pattern, followed by a marked increase during the pandemic and a slow decrease after the peak (see Appendix A).

Some retailers ordered smaller quantities than other retailers for a variety of reasons during the considered periods (e.g., lack of population density, distance from/to the location, very small subsidiary stores, etc.). The distributors can cease supplying these retailers to minimize disruptions in the SC and the total cost. Specifically, the first distributor can discard retailers 5, 6, 9, 11, 12, 13, 18, 20 and 21, and the second distributor can sever ties with retailers 3, 4, 6, 7, 8, 9, 10, 29, 30 and 31. Table 2 illustrates the total costs for each distributor after dispensing with the retailers with smaller orders. The total cost after discarding these retailers is clearly lower than the initial cost. For the first distributor, the total cost decreases by $4049, which represents 7% of the total cost. The cost for the second distributor decreases by $8891, which corresponds to 4.2% of the total cost. These percentages can be considered profit revenues. The aim of eliminating these retailers is to resolve the disruptions that occurred and prevent similar situations in the future, as well as enhance the SC's resilience to fulfil the orders of the remaining retailers.

6.2 ARIMA model

Before applying the ARIMA model, a seasonal procedure was piloted to test for seasonality fluctuations in the demand data. Figure 3 reveals clear seasonal patterns. The figure is

where $\widehat{\sigma}_{p,q}^2$ is the variance of the residual error. A smaller AIC indicates better fit when comparing fitted models. The procedures are clarified in Fig. 2.

5.4 Evaluating performance measures

To identify the optimal forecasting model, the performance of models can be measured through three standard evaluation methods: the mean absolute percentage error (MAPE), the root mean square error (RMSE) and the mean absolute error (MAE) (Dave et al. 2021; Satrio et al. 2021), which are given by the following equations:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| Y_t - \widehat{Y}_t \right|}{Y_t} \qquad (18)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Y_t - \widehat{Y}_t \right)^2} \qquad (19)$$
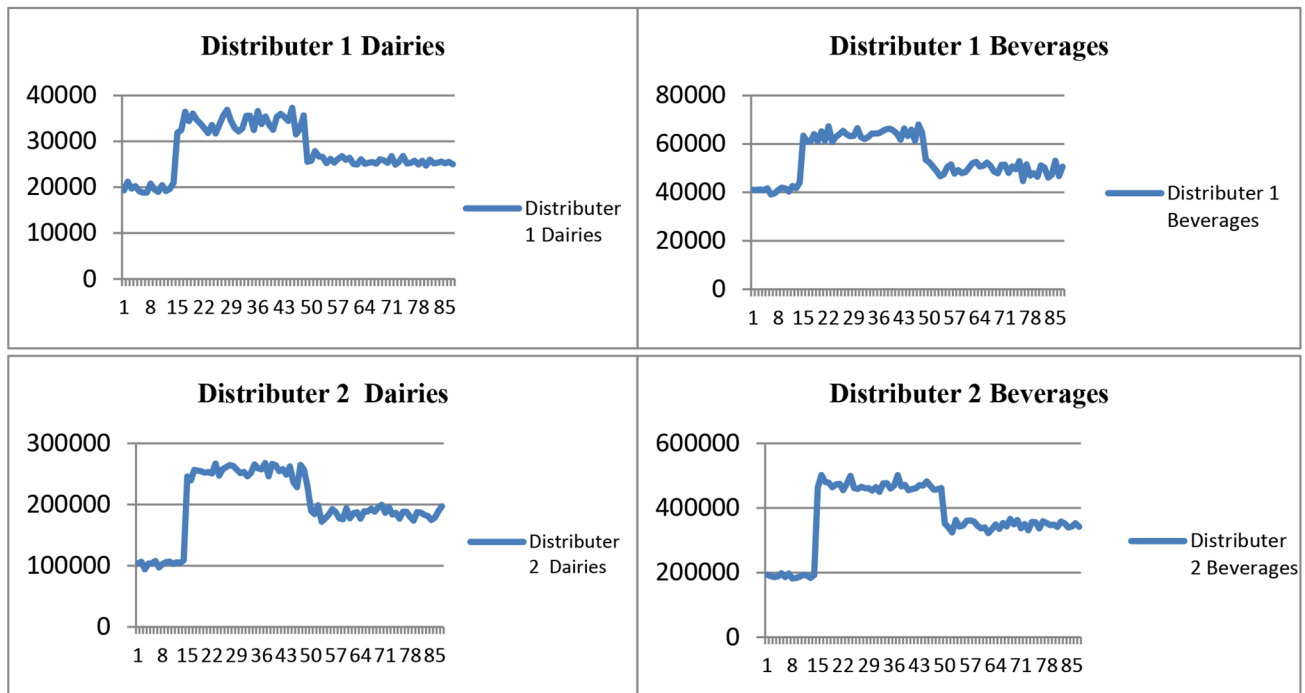
Fig. 3 Distributors' data fluctuations

divided into two parts, two distributors and two considered items (dairy foods & beverages).

Due to the seasonality apparent in Fig. 3, the ARIMA model is applied as a linear model to forecast the trend of the demand data utilizing Business Forecasting Solution for Business software version 3.8.9 (GMDH Shell 2018). Synchronization between the expected and real data gives the data linearity shown in Fig. 4.

Figure 4(a) & (c) present the results for the dairy food items for both distributors. The model starts forecasting from the third period of the considered data (after the pandemic peak/Lag 3) and predicts for the next 10 weeks in a linear manner. Many studies support a forecasting duration ranging from more than one month to six months (Satrio et al. 2021; Swaraj et al. 2021). Figure 4(b) & (d) present the results for the beverage items for both distributors. For these items, the model starts forecasting from the second period of the considered data (during the pandemic period/Lag 2) and predicts for the next 10 weeks in a linear manner. The ARIMA model ignores the period before the pandemic (Lag 1), which is reasonable because the SC disruptions began during and after the peak of the pandemic.

The next step is to evaluate the performance measures and the goodness of fit of the ARIMA model as assessed by *RMSE, MAE* and *MAPE* according to Eqs. (18–20) and by R^2 as shown in Table 3. High data forecasting accuracy of the ARIMA model is observed. Among the performance measures, the values of *MAPE* are smallest. The applied

ARIMA model has perfect accuracy in forecasting confirmed situations, with R^2 values of 0.98, 0.617, 0.603 and 0.93 for the items, respectively. This means that the distance between the real data and the regression line is very small, as greater positive values of R^2 indicate greater confidence and goodness of fit between the real data and forecasted data (Satrio et al. 2021).

7 Discussion

The COVID-19 outbreak has imposed major challenges on SCs worldwide, particularly in the food and beverages sector. These widespread SC disruptions have emphasized the need for distributors to adopt appropriate techniques to enhance SC resilience and increase their ability to foresee future situations. Several forecasting models have been suggested to predict demand fluctuations under pandemic conditions. Although the DES method is very appropriate for estimating the quantity of demand before, during and after the peak of the COVID-19 pandemic, it cannot sufficiently extract time-series patterns. Therefore, in this study, the use of the ARIMA model to predict potential future points of SC disruption is proposed. The objectives of this study are articulated by the three research questions. To address RQ1, the optimal order quantity and associated costs for each retailer were estimated for two distributors. The DES method was adopted to predict the demand lead time
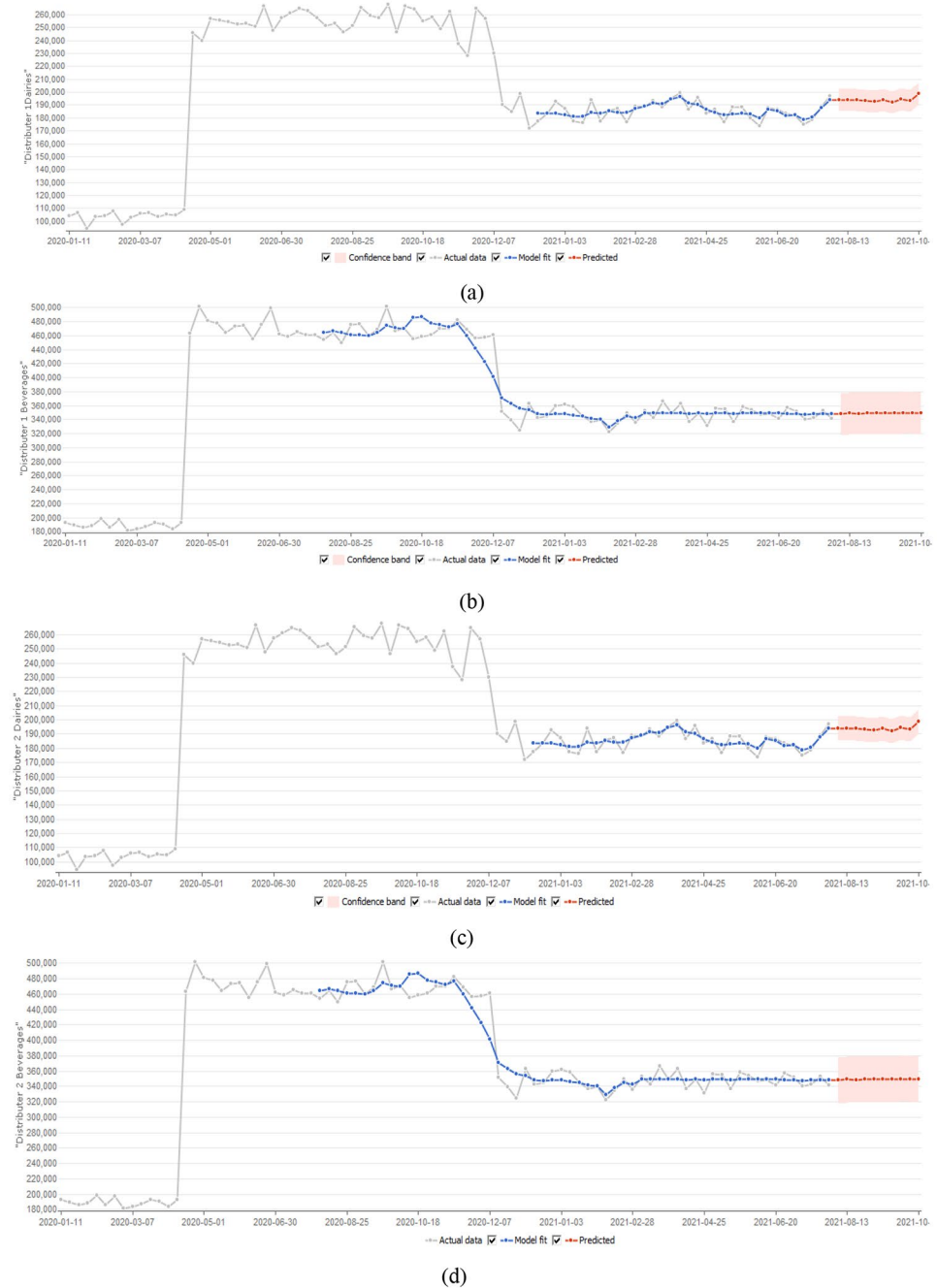
Fig. 4 ARIMA model

(a)

(b)

(c)

(d)

Table 3 Evaluating ARIMA models performance

Distributor	Items	ARIMA set			
		RMSE	MAE	MAPE	R^2
First	Dairy food	472.40	326.54	%1.94	0.9859
	Beverages	1334.6	1066.78	%2.16	0.617
Second	Dairy food	4283.01	3529.42	%1.91	0.603
	Beverages	14936.5	10576.3	%2.67	0.933

within a fixed lead time of one week. This method is suitable for forecasting seasonal data to detect SC disruptions arising from instability based on previous optimal order

quantities. The results indicate that distributors should dispense with retailers that ordered low quantities during the period under consideration. By omitting these retailers, the first and second distributor can decrease their total costs by 7% and 4.2%, respectively. The findings therefore confirm the literature regarding SC's resilience (Hobbs 2021; Lotfi and Larmour 2021; Pereira et al. 2021), and adding further clarification previously not empirically examined within the context of SC's resilience. However, it can stated that the findings are not restricted to unprecedented demand, but can

be more extended to the market responsiveness, providing new insights of doing business.

Next, in response to RQ2, the data were converted from seasonal to linear. The seasonality caused by the COVID-19 pandemic was responsible for the observed SC disruptions. To avoid these disruptions and enhance SC resilience, the ARIMA model was applied to give the best estimate of the predicted data and convert it to a stable linear model. Interestingly, the ARIMA model ignored the period before the pandemic (Lag 1), consistent with the onset of the SC disruptions during and after the peak of the pandemic. For both distributors, the proposed model started predictions and exhibited stability beginning from the second period (Lag 2) for beverages and the third period (Lag 3) for dairy foods. The findings indicate that SCs were not resilient or that they somehow failed to respond to the unexpected demand. Such findings enhance SC managers to expand their efforts beyond risk mitigation into establishing a more resilient SCs to predict the potential disruptions in the chain as a whole.

Finally, to address RQ3, measures for evaluating the performance of the proposed ARIMA model were assessed. According to analysis using *MAPE*, the accuracy of the model was high, with minimal differences between the real data and the forecasted data. Furthermore, the values of R^2 were high, indicating a perfect match and high confidence and quality of fit between the real data and the model's forecast. The findings demonstrate the need to develop the ability to anticipate and taking the required actions before the ability of the SC to function is affected particularly within a turbulent environment.

8 Theoretical implications

The severity of the COVID-19 pandemic has challenged our understanding of SC resilience built on the abundant SC resilience literature (Nikolopoulos et al. 2021). By addressing this research gap, this study has provided at least two contributions to the literature. First, by taking the distributor-retailer perspective, this study shifts the focus of research on SC disruptions from detection methods to predict the potential disruptions and response behaviors particularly in turbulent environments, which, in turn, reinforce the necessity of improving the adaptive capability of SCs to face unexpected conditions to help firms restore confidence and mitigate demand disruptions during the pandemic. A second contribution is that this study has strengthen the understanding of distributer-retailer coordination, by applying a robust applied methodology, which includes the collection of data from different periods of the pandemic, enhances the study's applicability to similar crises.

9 Managerial implications

The present analysis of demand fluctuation and its effects on SC resilience provides many important managerial implications. First, the disruption of SCs due to COVID-19 has been an unprecedented test of SC resilience. The full SC repercussions of COVID-19 are still unknown, and new SC challenges are likely even after the pandemic ends. Therefore, the findings suggest that the real cooperation between SC partners in the Kurdistan region of Iraq is essential to enable more precise and appropriate forecasting to optimize SC activities. Such optimization will influence many decisions, particularly those related to demand analysis, procurement costs, inventory levels and safety stock. Second, this study shows that the demand for food and beverages has been coupled to the severity of the pandemic, increasing the need to predict supply and inventory. Consequently, distributors and other SC managers in the Kurdistan region of Iraq are advised to adopt predictive methods, promote the exchange of up-to-date demand information among all SC partners, and activate the role of SCs as a source of competitive differentiation. In addition, distributors may consider developing a better relationship with their retailers and adopt more comprehensive incorporation to contain risk factors in the business they support. Finally, as the pandemic left store shelves full of unwanted products, SC managers are advised to increase their customer focus and align their strategies with customers' needs. Such an orientation is more likely to ensure highly resilient SCs that can meet customers' needs in a competitive manner. Therefore, distributors and retailers must be must share the critical information that enable them to create superior customer value.

10 Limitations and future research

This study has some limitations that should be considered in future research. First, data were collected only from the food and beverages sector, and the specific nature of this sector under pandemic conditions may act as a limitation. Future studies may collect data from different sectors to further empirically validate the findings. Second, as a further extension of this study, it would be interesting to include financial indicators, such as revenue level, for each product in the forecasting process. Finally, although the current study covered a sample of 56 retailers, it did not address the issue of transportation costs and distances between distributors and retailers. Therefore, it would be worthwhile to investigate the effect of this factor on demand and total costs.

11 Conclusion

This study aimed to determine the best forecasting model for demand volatility in the context of foods and beverages over three periods of disruption using a time-series model. Models based on DES and ARIMA were developed and found to be valid and appropriate for forecasting seasonal volatility. The findings confirmed the disruptive effect of COVID-19 on demand since the outbreak of the epidemic through 31 July 2021. These findings also emphasize the need for a reliable prediction tool to support decision-making processes for SC resilience and survival during and after turbulent events. Finally, this study provides an opportunity for business partners to recognize the exchange of demand information as a mechanism to build more resilient SCs and avoid serious disruptions. It is hoped that this study will help scholars and practitioners to focus more on the potential opportunities to bridge the gap between SC resilience research and industry practice.

12 Appendix A. Optimal q* and its total cost, TC

Retailers and items		First distributer		Second distributer	
		q^*	TC ($)	q^*	TC($)
Retailer 1	Dairy food Items	6180	1545	21,000	7350
	Beverages Items	12,342	1851	33,579	7052
Retailer 2	Dairy food Items	8938	2235	18,713	6650
	Beverages Items	14,925	2239	33,579	7052
Retailer 3	Dairy food Items	3131	783	165	181
	Beverages Items	4834	725	318	111
Retailer 4	Dairy food Items	3747	937	250	195
	Beverages Items	4241	636	599	378
Retailer 5	Dairy food Items	185	263	14,637	5123
	Beverages Items	278	218	20,929	4395
Retailer 6	Dairy food Items	90	124	321	287
	Beverages Items	211	173	399	231
Retailer 7	Dairy food Items	685	171	265	163
	Beverages Items	1508	226	314	213
Retailer 8	Dairy food Items	1137	284	164	407
	Beverages Items	2311	347	102	378
Retailer 9	Dairy food Items	160	300	469	339
	Beverages Items	253	380	566	329
Retailer 10	Dairy food Items	11,506	2876	384	484
	Beverages Items	20,361	3054	573	435
Retailer 11	Dairy food Items	221	553	13,282	4649
	Beverages Items	240	430	24,779	5204
Retailer 12	Dairy food Items	133	198	8030	2810
	Beverages Items	315	276	12,042	2529
Retailer 13	Dairy food Items	246	380	5915	2070
	Beverages Items	448	281	10,437	2192

Retailers and items		First distributer		Second distributer	
		q^*	TC ($)	q^*	TC($)
Retailer 14	Dairy food Items	8461	2115	11,046	3866
	Beverages Items	16,665	2500	17,286	3630
Retailer 15	Dairy food Items	13,861	3465	6087	2130
	Beverages Items	22,252	3338	15,485	3252
Retailer 16	Dairy food Items	5495	1374	19,983	6994
	Beverages Items	10,701	1605	28,667	6020
Retailer 17	Dairy food Items	1880	470	12,848	4497
	Beverages Items	2901	435	28,445	5973
Retailer 18	Dairy food Items	103	159	8547	2992
	Beverages Items	170	156	5640	1184
Retailer 19	Dairy food Items	4558	1139	7683	2689
	Beverages Items	6920	1038	25,566	5369
Retailer 20	Dairy food Items	84	111	3119	1092
	Beverages Items	212	180	6459	1356
Retailer 21	Dairy food Items	467	450	15,974	5591
	Beverages Items	400	420	22,474	4720
Retailer 22	Dairy food Items	3759	940	28,554	9994
	Beverages Items	7519	1128	53,253	11,183
Retailer 23	Dairy food Items	7333	1833	27,003	9451
	Beverages Items	14,097	2115	44,258	9294
Retailer 24	Dairy food Items	11,513	2878	5710	1999
	Beverages Items	20,273	3041	13,027	2736
Retailer 25	Dairy food Items	8764	2191	8526	2984
	Beverages Items	20,065	3010	15,848	3328
Retailer 26	Dairy food Items	——	——	11,554	4044
	Beverages Items	——	——	16,997	3569
Retailer 27	Dairy food Items	——	——	31,768	7942
	Beverages Items	——	——	46,795	9827
Retailer 28	Dairy food Items	——	——	7371	2580
	Beverages Items	——	——	23,715	4980
Retailer 29	Dairy food Items	——	——	706	947
	Beverages Items	——	——	476	1906
Retailer 30	Dairy food Items	——	——	653	334
	Beverages Items	——	——	827	384
Retailer 31	Dairy food Items	——	——	782	624
	Beverages Items	——	——	796	566

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