Chapter 14
Quick Response Fashion Supply Chains in the Big Data Era

Tsan-Ming Choi

Abstract The quick response strategy has been widely adopted in the fashion industry. With a shortened lead time, quick response allows fashion supply chain members to conduct forecast information updating which helps to reduce demand uncertainty. In the big data era, forecast information updating is even more effective as more data points can be collected easily to improve forecasting. In this paper, after reviewing the related literature, we explore how the quick response strategy with *n* observations can improve the whole fashion supply chain's performance. We study how the number of observations affects the expected values of quick response for the fashion supply chain, the fashion retailer, and the fashion manufacturer. Then, we analytically how the robust win–win coordination can be achieved in the quick response fashion supply chain using the commonly seen wholesale pricing markdown contract. Insights are generated.

Keywords Bayesian information updating • Quick response • Supply chain coordination • Supply chain optimization • Use of information

14.1 Introduction and Related Literature

Quick response is a well-established strategy in fashion supply chain management. The first proposal on the implementation of quick response started in the USA in the 1980s by the fashion manufacturers (Fisher and Raman 1996; Iyer and Bergen 1997; Choi et al. 2003; Choi and Chow 2008). After decades of evolution, quick response is now a critical measure to achieve business models such as fast fashion (Cachon and Swinney 2011).

One basic element of all quick response programs is the reduction of lead time (Choi et al. 2004, 2006). As a matter of fact, by reducing lead time, more market signals (Shaltayev and Sox 2010) can be observed and incorporated into

T.-M. Choi (✉)
Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong
e-mail: jason.choi@polyu.edu.hk

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the demand forecasting process. This leads to a more accurate forecast[1]. Based on a more accurate forecast, inventory planning becomes more precise and the respective supply chain system is more efficient. This is an especially important measure for industries which face highly volatile demand, such as fashion apparel.

In the big data era, a massive amount of data is available (Chan et al. 2016). Data collection is also made easier (Choi et al. 2016a). As a result, in quick response, fashion companies can easily make use of the large amount of related data to improve forecast. This would make quick response an even more significant measure to improve the supply chain system's performance. However, two challenges exist: (1) Even though quick response can significantly enhance the supply chain's profitability, the supply chain system itself will not be optimal by itself owing to the double marginalization problem (Donohue 2000; Chiu et al. 2011; Choi 2016c); (2) it is a well-known fact that quick response implementation need not be win–win to the supplier and the buyer (Iyer and Bergen 1997).

In light of these two challenges and the convenience of having a lot of market observations (i.e., n observations) under quick response[2], this paper is developed. The focal points of this paper include: (1) Examining how the number of observations affects the expected values of quick response for the fashion supply chain, the fashion retailer, and the fashion manufacturer; (2) uncovering analytically how the win–win coordination outcome can be achieved after implementing quick response by the wholesale pricing markdown contract. Both academic and managerial insights are developed.

For the related literature, as quick response in supply chain management is a big topic, we examine some recently published related papers as follows and refer readers to the review by Choi and Sethi (2010) for the other older studies. First, in the operations-marketing interface, Cachon and Swinney (2011) explore how the quick response strategy supports the fast fashion business model in the presence of forward looking consumers. Yang et al. (2011) explore the supply chain with a single retailer and two suppliers with different lead times. Forecast updating is feasible before the retailer orders from the short lead time (i.e., quick response) supplier. The authors reveal how the supply chain with forecast updating can be coordinated. Then, in a competitive environment, Lin and Parlakturk (2012) study via a game-theoretic model how competition affects the performance of quick response. Choi (2013) studies the impacts of imposing carbon emission tax on fashion quick response systems and argues that carbon emission tax is an effective means to entice retailers to source locally. Liu and Nagurney (2013) explore a global sourcing problem. The authors consider both demand and cost uncertainties and discuss how quick response performs. Other recent studies related to quick response include: a study on the quick response system in the presence of loss-averse strategic

[1]This concept is in line with the "advance booking scheme" (see, e.g., McCardle et al. 2004).

[2]Notice that different from Choi (2007), this paper considers the situation when n observations can be collected all within the same period of time whereas Choi (2007) considers multiple observations at different time durations.

consumers (Lee et al. 2015), an exploration on the coordination challenge in supply chains with multiple shipments during the season (Chen et al. 2016b), an analysis of the risk averse behaviors on quick response systems (Choi 2016a), an investigation on how social media information affects the performance of quick response system in the presence of boundedly rational retailers (Choi 2016b), and a case study on how quick response manufacturing complements lean supply chain operations (Fernando J. Gómez and Filho 2016).

Notice that similar to all the above papers, this paper focuses on quick response. Similar to most reviewed papers, such as Iyer and Bergen (1997), Choi et al. (2003, 2004), Kim (2003), Choi (2007, 2016a, b, c), this paper also employs the Bayesian normal conjugate pair model in the analysis. However, different from all of them, this paper considers the case when n observations can be collected for the forecast updating and investigates how the large number of observations affects the performance of quick response. In this regard, this paper is closest to the paper by Chan et al. (2015) which also considers the problem of having multiple observations. However, in Chan et al. (2015), observations are expensive and hence the authors discuss the optimal number of sampling whereas in this paper, the number of observations "n" is taken as a parameter and we examine the performance of quick response when n increases and when it goes to infinity (and hence follows the trend in the "big data" era).

This paper is organized as follows. First, we present the basic inventory model and the Bayesian information updating model in Sect. 14.2. Then, we explore the performance of the centralized supply chain system under quick response in Sect. 14.3. After that, we investigate the impacts brought by quick response in the decentralized supply chain in Sect. 14.4. We report how the win–win coordination scenario can be achieved by using the wholesale pricing markdown contract in Sect. 14.5. Finally, we conclude the paper with a discussion of future research in Sect. 14.6.

14.2 Basic Model

14.2.1 Inventory Model

We employ the newsvendor problem (Chen et al. 2016a) to model the inventory model for the fashion product. To be specific, before the selling season starts, we consider the case where a fashion retailer needs to order a certain quantity q of a seasonal fashion product (e.g., a colorful tee) from its supplier, which is a fashion manufacturer, with a unit product ordering cost c. The fashion supplier operates as a follower and it will start production only after receiving the order from the fashion retailer. The fashion retailer sells the product in the market with a unit retail selling price r, and the supplier produces the product at a unit cost p. For the unsold product, for the sake of simplicity, we assume that the holding cost and the salvage value together would lead to a net salvage value v. To avoid trivial cases, we have $r > c > p > v$. The seasonal fashion product's demand is uncertain and follows a distribution which is described in the next sub-section.

14.2.2 Bayesian Information Updating

In this sub-section, we present the demand distribution. As we consider the quick response strategy in this paper, we would consider two time points. To be specific, suppose that the fashion retailer used to order from the supplier with a long lead time at Time 0. In this ordering time point, as the fashion retailer possesses relatively rough forecast regarding the real seasonal demand for the product, the respective demand uncertainty is high. Now, if the supplier allows the fashion retailer to order at a time point with a shorter lead time, called Time 1, the fashion retailer can make use of market observations to improve its forecast. In this paper, we consider the case when the fashion retailer can collect and use a sufficient amount of market information so that the demand uncertainty is much reduced.

Following the standard definition of quick response (see Choi and Chow 2008; Choi 2016a, b, c), we refer the ordering at Time 1 as the one under quick response (QR) whereas the ordering at Time 0 is under slow response (SR).

To model the above relationship, we employ the Bayesian theory (Iyer and Bergen 1997; Kim 2003) with the normal conjugate pair. First, we denote the predicted demand of the product at Time 0 by x_0. Following the basic demand uncertainty structure as shown in the literature (see Iyer and Bergen 1997; Choi and Chow 2008; Choi 2016a, b, c) we model the distribution of x_0 as a normal distribution with mean θ and variance δ in the following: $x_0 \;\; N(\theta, \delta)$. Notice that δ represents the inherent demand volatility of the seasonal fashion product and it is not reducible by market observation. For θ, the mean of demand at Time 0, we model it as a random variable which also follows a normal distribution, with mean μ_0 and variance d_0:

$$\theta \sim N(\mu_0, d_0).$$

At Time 0, with the above formulation, it is known that the unconditional distribution of x_0 is a normal distribution with mean μ_0 and variance $(d_0 + \delta)$,

$$x_0 \sim N(\mu_0, d_0 + \delta).$$

The above demand model captures the demand distribution of the seasonal fashion product if the fashion retailer orders at Time 0, i.e., under SR.

We now explore QR and denote the predicted demand at Time 1 by x_1. In the big data era, collecting data is easy and we assume that the fashion retailer can quickly and conveniently collect a massive amount of related market observations of products following the same normal process (P.S.: we represent the number of observations as n) between Time 0 and Time 1. Using the Bayesian conjugate pair theory, this leads to the following unconditional distribution for x_1 as follows (e.g., see Chan et al. 2015):

$$x_1 \sim N\left(\mu_1(n), d_1(n) + \delta\right),$$

where

$$\mu_1(n) = \left(\frac{\delta\mu_0 + nd_0 o}{nd_0 + \delta}\right),$$

$$d_1(n) = \frac{d_0\delta}{nd_0 + \delta},$$

and o is the mean of the n observations.

Notice that the Bayesian conjugate pair demand model proposed above is not new and it is a standard result in the literature. This paper simply follows and uses it for further analysis. From the above model, we have Lemma 2.1.

Lemma 2.1. *(a) Comparing the levels of demand uncertainty (measured by demand variance) under QR and SR, with n-observation based information updating, the demand uncertainty under QR is smaller and the reduction is increasing in n.*

(b) When $n \to \infty$, demand uncertainty under QR (measured by demand variance) becomes δ.

Proof of Lemma 2.1. All proofs are placed in the appendix.

Lemma 2.1 shows that the market observation can improve forecasting via the Bayesian information updating process. In addition, when we take more observations and incorporate them into the forecast revision, the significance of QR is higher. At the extreme, when the number of observations goes to infinity, all the reducible demand uncertainty vanishes and the remaining demand uncertainty is simply equal to the inherent demand uncertainty δ which cannot be reduced further.

For a notational purpose: We employ $\varphi(\cdot)$, $\Phi(\cdot)$, and $\Psi(x) = \int_x^\infty (y - x)\,\varphi(y)dy$ to represent the standardized normal density function, standardized normal cumulative distribution function, and linear loss function with the standard normal distribution, respectively. The inverse function of $\Phi(\cdot)$ is represented by $\Phi^{-1}(\cdot)$. Table 14.1 shows a summary of the major notation employed in this paper.

14.3 Centralized Supply Chain

From Sect. 14.2, we have already reviewed and presented the model with the consideration of Bayesian information updating. In the following, we conduct analysis on the performance of QR focusing on the centralized supply chain system. The analysis result will be used as a benchmark for the further exploration in Sect. 14.4.

Table 14.1 Notation

Notation	Meaning
QR	Quick response
SR	Slow response
R	Fashion retailer
S	Fashion supplier
SC	Fashion supply chain
EP	Expected profit
q	Quantity
EVQR	Expected value of QR
r	Unit retail price
c	Unit wholesale price
p	Unit production cost
v	Unit net salvage value
n	Number of observations
WPM	Wholesale pricing markdown
Ω	WPM contract
$\widehat{c}$	Unit wholesale price in Ω
$\widehat{m}$	Unit markdown sponsor in Ω

First of all, adopting the same approach as in Iyer and Bergen (1997), we can easily derive the fashion supply chain (SC)'s optimal ordering quantity if ordering is placed at Time 0 (i.e., under SR) as follows:

$$q_{0,SC*} = \mu_0 + \sqrt{d_0 + \delta}\Phi^{-1}\left[(r-p)\,/\,(r-v)\right]. \tag{14.1}$$

Notice that (14.1) follows the standard "critical fractile" expression as in the standard newsvendor problem.

Denote $s_{SC} = (r-p)/(r-v)$. With (14.1), the corresponding optimal fashion supply chain's expected profit when the ordering is placed at Time 0 (i.e., under SR) can be found to be the following:

$$EP_{0,SC*} = (r-p)\,\mu_0 - \sqrt{d_0 + \delta}T_{SC}\left(s_{SC}\right), \tag{14.2}$$

where

$$T_{SC}\left(s_{SC}\right) = (p-v)\,\Phi^{-1}\left(s_{SC}\right) + (r-v)\,\Psi\left[\Phi^{-1}\left(s_{SC}\right)\right]. \tag{14.3}$$

If the ordering is placed at Time 1 with the updated mean of demand $\mu_1(n)$, the optimal fashion supply chain quantity and the corresponding optimal fashion supply chain expected profit are shown below:

$$q_{1,SC*}\Big|\mu_1(n) = \mu_1(n) + \sqrt{d_1(n) + \delta}\Phi^{-1}\left[(r-p)\,/\,(r-v)\right]. \tag{14.4}$$

$$EP_{1,SC*}\Big|\mu_1(n) = (r-p)\,\mu_1(n) - \sqrt{d_1(n) + \delta}T_{SC}\left(s_{SC}\right), \tag{14.5}$$

Un-conditioning (14.4) and (14.5) with respect to $\mu_1(n)$ yields the following expected optimal fashion supply chain quantity and optimal fashion supply chain expected profit at Time 0:

$$q_{1,SC*} = \mu_0 + \sqrt{d_1(n) + \delta}\Phi^{-1}\left[(r-p)/(r-v)\right], \tag{14.6}$$

$$EP_{1,SC*} = (r-p)\,\mu_0 - \sqrt{d_1(n) + \delta}T_{SC}\left(s_{SC}\right). \tag{14.7}$$

Define the expected value of quick response for the fashion supply chain system as follows: $EVQR_{SC}(n) = EP_{1,SC_*} - EP_{0,SC_*}$. We have the following expression for $EVQR_{SC}(n)$ and Lemma 3.1:

$$EVQR_{SC}(n) = \left(\sqrt{d_0 + \delta} - \sqrt{d_1(n) + \delta}\right) T_{SC}\left(s_{SC}\right). \tag{14.8}$$

Lemma 3.1. *(a) From the centralized supply chain perspective, adopting QR is always beneficial because* $EVQR_{SC}(n) > 0$.

(b) $EVQR_{SC}(n)$ *is increasing in n.*

(c) When $n \to \infty$, $EVQR_{SC}(n \to \infty) = \left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) T_{SC}\left(s_{SC}\right)$.

Lemma 3.1 shows that in the centralized fashion supply chain, QR is always a beneficial measure and it gives a positive expected gain in profit to the supply chain. In addition, when the number of observations increases, the expected gain by using QR for the fashion supply chain is even higher. When the number of observations goes to infinity, the maximum amount of expected gain for the supply chain by using QR is shown in Lemma 3.1c.

14.4 Decentralized Supply Chain

In Sect. 14.3, we have examined the centralized case and revealed that QR is always beneficial to the supply chain system. In this section, we explore the expected profits for the fashion retailer and the fashion manufacturer under a decentralized setting.

First, it is straightforward to find the fashion retailer (R)'s optimal ordering quantity if the order is placed at Time 0 (i.e., under SR):

$$q_{0,R*} = \mu_0 + \sqrt{d_0 + \delta}\Phi^{-1}\left[(r-c)/(r-v)\right]. \tag{14.9}$$

Denote $s_R = (r-c)/(r-v)$. With (14.9), if the order is placed at Time 0, the corresponding optimal fashion retailer's expected profit can be derived to be the following:

$$EP_{0,R*} = (r-c)\,\mu_0 - \sqrt{d_0 + \delta}T_R\left(s_R\right), \tag{14.10}$$

where

$$T_R\left(s_R\right) = (c - v)\,\Phi^{-1}\left(s_R\right) + (r - v)\,\Psi\left[\Phi^{-1}\left(s_R\right)\right]. \tag{14.11}$$

The fashion supplier's expected profit is listed as follows if the fashion retailer orders at Time 0:

$$EP_{0,S*} = (c - p)\left(\mu_0 + \sqrt{d_0 + \delta}\,\Phi^{-1}\left(s_R\right)\right). \tag{14.12}$$

If the ordering is placed at Time 1 with the updated mean of demand $\mu_1(n)$, the optimal fashion retailer's ordering quantity, and the corresponding optimal fashion retailer's expected profit and the fashion supplier's expected profit are listed below:

$$q_{1,R*}\Big|\mu_1(n) = \mu_1(n) + \sqrt{d_1(n) + \delta}\,\Phi^{-1}\left(s_R\right), \tag{14.13}$$

$$EP_{1,R*}\Big|\mu_1(n) = (r - c)\,\mu_1(n) - \sqrt{d_1(n) + \delta}\,T_R\left(s_R\right), \tag{14.14}$$

$$EP_{1,S*}\Big|\mu_1(n) = (c - p)\left(\mu_1(n) + \sqrt{d_1(n) + \delta}\,\Phi^{-1}\left(s_R\right)\right). \tag{14.15}$$

Un-conditioning (14.13)–(14.15) with respect to $\mu_1(n)$ yields the following:

$$q_{1,R*} = \mu_0 + \sqrt{d_1(n) + \delta}\,\Phi^{-1}\left(s_R\right), \tag{14.16}$$

$$EP_{1,R*} = (r - c)\,\mu_0 - \sqrt{d_1(n) + \delta}\,T_R\left(s_R\right), \tag{14.17}$$

$$EP_{1,S*} = (c - p)\left(\mu_0 + \sqrt{d_1(n) + \delta}\,\Phi^{-1}\left(s_R\right)\right). \tag{14.18}$$

Define the expected values of quick response for the fashion retailer and the fashion supplier as follows:

$$EVQR_R(n) = EP_{1,R*} - EP_{0,R*},$$

$$EVQR_S(n) = EP_{1,S*} - EP_{0,S*}.$$

After simplification, we have:

$$EVQR_R(n) = \left(\sqrt{d_0 + \delta} - \sqrt{d_1(n) + \delta}\right) T_R\left(s_R\right), \tag{14.19}$$

$$EVQR_S(n) = -\,(c - p)\left(\sqrt{d_0 + \delta} - \sqrt{d_1(n) + \delta}\right) \Phi^{-1}\left(s_R\right). \tag{14.20}$$

The properties of $EVQR_R(n)$ and $EVQR_S(n)$ are summarized in Lemmas 4.1 and 4.2.

Lemma 4.1. *(a) In the decentralized supply chain, adopting QR is always beneficial for the fashion retailer because* $EVQR_R(n) > 0$.

(b) $EVQR_R(n)$ *is increasing in n.*

(c) When $n \to \infty$, $EVQR_R(n \to \infty) = \left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) T_R\,(s_R)$.

Lemma 4.2. *(a) In the decentralized supply chain, adopting QR is NOT always beneficial for the fashion supplier because* $EVQR_S(n) > 0$ *if and only if* $s_R < 0.5$*, and* $EVQR_S(n) \leq 0$ *if and only if* $s_R \geq 0.5$.

(b) $EVQR_S(n)$ *is increasing in n if and only if* $s_R < 0.5$*, and* $EVQR_S(n)$ *is decreasing in n if and only if* $s_R \geq 0.5$.

(c) When $n \to \infty$, $EVQR_S(n \to \infty) = -\,(c - m)\left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) \Phi^{-1}\,(s_R)$.

Lemmas 4.1 and 4.2 show that in the decentralized supply chain, QR is always a beneficial measure to the fashion retailer but it may not be good for the fashion supplier. For the fashion retailer, the case is similar to the centralized supply chain case: when the number of observations increases, the expected value of QR for the fashion retailer becomes higher and the maximum value is equal to $\left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) T_R\,(s_R)$. For the fashion supplier, whether QR is beneficial or not depends on the inventory service level s_R (which is the same as what the literature shows (see, e.g., Iyer and Bergen (1997); Choi (2016c)). When the inventory service level is very low (i.e., $s_R < 0.5$), QR is beneficial to the fashion supplier; otherwise, QR hurts the fashion supplier's expected profit. Depending on the value of inventory service level, the effect brought by the number of observations n varies. To be specific, as shown by Lemma 4.2b, QR is a more beneficial measure when n increases if the inventory service level is very low (i.e., $s_R < 0.5$); otherwise, QR is less beneficial when n increases. Moreover, when the number of observations goes to infinity, Lemma 4.2c shows that the expected value of QR for the fashion supplier is finite and it becomes $-\,(c - m)\left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) \Phi^{-1}\,(s_R)$.

Furthermore, by checking the quantity decisions in (14.1), (14.6), (14.9), and (14.16), we have Lemma 4.3.

Lemma 4.3. *When* $c > p$*, we have:* $q_{0,R*} < q_{0,SC*}$ *and* $q_{1,R*}|\mu_1(n) < q_{1,SC*}|\mu_1(n)$.

Lemma 4.3 indicates that for every time point, the fashion retailer's optimal ordering quantity (under the decentralized setting) is different from the fashion supply chain's optimal ordering quantity (under the centralized setting). This is an intuitive result because the fashion retailer faces a different and lower profit margin compared to the fashion supply chain system. As a result, it is natural for the existence of different optimal quantities in which the fashion retailer will order a smaller amount compared to the supply chain system counterpart. This follows the classic double marginalization theory (Spengler 1950) in the literature.

14.5 Win–Win Coordination

In Sects. 14.3 and 14.4, we have found that QR is a good strategy to improve the fashion supply chain's performance. However, in a decentralized setting, not only does the supply chain fail to be optimal, but the fashion supplier may also suffer a loss after adopting QR. In this section, we propose how a commonly seen wholesale pricing markdown (WPM) contract can be applied to achieve win–win coordination for the fashion supply chain upon its implementation of QR.

Under the WPM contract, we consider the case when the fashion supplier offers a unit wholesale price $\widehat{c}$ and a unit markdown sponsor $\widehat{m}$ to the fashion retailer at Time 1 under QR. We denote this WPM contract by: $\Omega\left(\widehat{c},\widehat{m}\right)$. To be specific, in the presence of the WPM contract, when the fashion retailer has leftover, the fashion supplier is willing to provide a unit sponsor of $\widehat{m}$ for all the product leftover. This sponsor directly reduces the risk faced by overstocking and can entice the fashion retailer to order more. Notice that the WPM contract is commonly seen in the fashion industry (see Shen et al. 2016).

In the presence of $\Omega\left(\widehat{c},\widehat{m}\right)$, the unconditional expected profit of the fashion retailer, the fashion retailer's optimal ordering quantity under QR, and the unconditional expected profit of the fashion supplier are given as follows:

$$EP^{\Omega}_{1,R*} = \left(r-\widehat{c}\right)\mu_0 - \sqrt{d_1(n)+\delta}T^{\Omega}_{R}\left(s^{\Omega}_{R}\right), \tag{14.21}$$

where

$s^{\Omega}_{R} = \left(r-\widehat{c}\right)/\left(r-\widehat{m}-v\right), and,$ and $T^{\Omega}_{R}\left(s^{\Omega}_{R}\right) = \left(\widehat{c}-\widehat{m}-v\right)\Phi^{-1}\left(s^{\Omega}_{R}\right) + \left(r-\widehat{m}-v\right)\Psi\left[\Phi^{-1}\left(s^{\Omega}_{R}\right)\right],$

$$q^{\Omega}_{1,R*}\Big|\mu_1(n) = \mu_0 + \sqrt{d_1(n)+\delta}\,\Phi^{-1}\left(s^{\Omega}_{R}\right),$$

$$\begin{aligned} EP^{\Omega}_{1,S*} = \left(\widehat{c}-p\right)&\left[\mu_0 + \sqrt{d_1(n)+\delta}\,\Phi^{-1}\left(s^{\Omega}_{R}\right)\right] \\ &- \widehat{m}\sqrt{d_1(n)+\delta}\left[\Phi^{-1}\left(s^{\Omega}_{R}\right) + \Psi\left\{\Phi^{-1}\left(s^{\Omega}_{R}\right)\right\}\right]. \end{aligned}$$

Define the following:

$$EVQR^{\Omega}_{R}(n) = EP^{\Omega}_{1,R*} - EP_{0,R*},$$

$$EVQR^{\Omega}_{S}(n) = EP^{\Omega}_{1,S*} - EP_{0,S*}.$$

After simplification, we have:

$$EVQR^{\Omega}_{R}(n) = \left(c-\widehat{c}\right)\mu_0 + \sqrt{d_0+\delta}T_R\left(s_R\right) - \sqrt{d_1(n)+\delta}T^{\Omega}_{R}\left(s^{\Omega}_{R}\right), \tag{14.22}$$

$$EVQR_S^{\Omega}(n) = (\widehat{c}-c)\,\mu_0 + (\widehat{c}-p)\,\sqrt{d_1(n)+\delta}\,\Phi^{-1}\left(s_R^{\Omega}\right) - (c-p)\,\sqrt{d_0+\delta}\,\Phi^{-1}\left(s_R\right)$$
$$- \widehat{m}\sqrt{d_1(n)+\delta}\left[\Phi^{-1}\left(s_R^{\Omega}\right) + \Psi\left\{\Phi^{-1}\left(s_R^{\Omega}\right)\right\}\right]. \tag{14.23}$$

To achieve win–win coordination in the supply chain after adopting QR, we have to ensure the following three conditions are met:

$$EVQR_R^{\Omega}(n) > 0, \tag{14.24}$$

$$EVQR_S^{\Omega}(n) > 0, \tag{14.25}$$

$$q_{1,R*}^{\Omega}\,|\mu_1(n) = q_{1,SC*}|\,\mu_1(n). \tag{14.26}$$

Observe that the conditions in (14.24) and (14.25) guarantee that the win–win outcome appears because both the fashion retailer and the fashion supplier are benefited under QR. The condition of (14.26) ensures the fashion retailer will order the quantity which is the best for the whole supply chain system.

In order to derive the win–win coordinating WPM contract, we define the following and present Lemma 5.1:

$$m* = (\widehat{c}-p)\,(r-v)\,/\,(r-p)\,, \tag{14.27}$$

$$c_{upper} = \arg_{\widehat{c}}\left\{EVQR_R^{\Omega}\,(n|\widehat{m} = m*) = 0\right\}, \tag{14.28}$$

$$c_{lower} = \arg_{\widehat{c}}\left\{EVQR_S^{\Omega}\,(n|\widehat{m} = m*) = 0\right\}. \tag{14.29}$$

Lemma 5.1. *(a)* $\widehat{m} = m*$ *if and only if* $q_{1,R*}^{\Omega}\Big|\mu_1(n) = q_{1,SC_*}|\mu_1(n)$.

(b) $EVQR_R^{\Omega}\,(n|\widehat{m} = m*)$ *is a decreasing function of* $\widehat{c}$*, and* $EVQR_S^{\Omega}\,(n|\widehat{m} = m*)$ *is an increasing function of* $\widehat{c}$*.*

Lemma 5.1 gives the important result and structural properties for deriving the coordinating WPM contract. First, Lemma 5.1a shows that by setting $\widehat{m} = m*$ under QR, supply chain coordination is achieved in which the fashion retailer will order a quantity the same as the optimal quantity for the whole supply chain system. Thus, by substituting $\widehat{m} = m*$ into $EVQR_R^{\Omega}(n)$ and $EVQR_S^{\Omega}(n)$ helps to reduce the dimension of setting the coordinating WPM contract from two dimensions $(\widehat{c}, \widehat{m})$to one dimension $(\widehat{c})$. Second, Lemma 5.1b shows the monotonic structural properties of $EVQR_R^{\Omega}\,(n|\widehat{m} = m*)$ and $EVQR_S^{\Omega}\,(n|\widehat{m} = m*)$. From them, we know that $c_{upper}$and c_{lower} give the upper and lower bound for setting the wholesale price $(\widehat{c})$of the win–win coordinating WPM contract (and the corresponding $\widehat{m}$ can be found by using (14.28)).

Based on Lemma 5.1, we present Lemma 5.2 on the setting of contract parameters to achieve win–win coordination for QR implementation by using the WPM contract.

Lemma 5.2. *After the QR implementation, win–win coordination can be achieved by setting* $\widehat{m} = m*$ *and* $c_{lower} < \widehat{c} < c_{upper}$.

From Lemma 5.2, we can see that: (1) there exist an infinite number of the WPM contracts which can achieve win–win coordination (because any $\widehat{c}$ in the range of $c_{lower} < \widehat{c} < c_{upper}$, together with the corresponding $\widehat{m} = m*$ will do). The specific setting depends on the bargaining power of the fashion retailer and the fashion supplier. When $\widehat{c}$ is set closer to c_{upper}, the fashion retailer's expected gain from QR drops whereas the fashion supplier's expected gain from QR increases. When $\widehat{c}$ is set closer to c_{lower}, the opposite happens. Thus, we see that the proposed WPM contract is rather robust which can divide the expected gain from QR in the supply chain system flexibly between the fashion retailer and the fashion supplier.

14.6 Conclusion

QR is a well-established and important industrial practice in the fashion industry. Motivated by the importance of QR and the availability of a huge amount of data, we have examined in this paper the value of QR (with forecast information updating) in fashion supply chains in the big data era. We have proven how the quick response strategy with n observations can help improve the whole fashion supply chain's performance. We have shown how the number of observations affects the expected values of QR for the fashion supply chain, the fashion retailer, and the fashion manufacturer. To be specific, we have demonstrated analytically that under QR, if the number of observations increases, the expected values of QR for the fashion supply chain (under the centralized model) and the fashion retailer (under the decentralized model) will both increase and reach the finite maximum when the number of observations goes to infinity. For the fashion supplier, the situation depends on the inventory service level and a larger number of observations can lead to an increase or a reduction of the expected value of QR (see Table 14.2).

After that, we have discussed how the win–win coordination after implementing QR can be achieved using the WPM contract. The proper setting of the contract

Table 14.2 Impacts of n on EVQRs

	Centralized	Decentralized	
	$EVQR_{SC}(n)$	$EVQR_R(n)$	$EVQR_S(n)$
$n\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$ *iff* $s_R < 0.5$ $\downarrow$ *iff* $s_R \geq 0.5$
$n \to \infty$	$\left(\sqrt{d_0+\delta}-\sqrt{\delta}\right) T_{SC}\left(s_{SC}\right)$	$\left(\sqrt{d_0+\delta}-\sqrt{\delta}\right) T_R\left(s_R\right)$	$-(c-m)\left(\sqrt{d_0+\delta}-\sqrt{\delta}\right) \Phi^{-1}\left(s_R\right)$

parameters as well as the analytical bounds has been derived. We have revealed that the win–win coordinating WPM contract is quite robust as it not only can guarantee the achievability of win–win coordination, but it also can divide the expected gain from QR of the supply chain system flexibly between the seller (i.e., the fashion supplier) and the buyer (i.e., the fashion retailer).

For future research, one can extend the model to cover the case when there are multiple products and explore the corresponding coordination challenges. In addition, the consideration of social media data for QR is also interesting and Choi (2016b) provides a good reference for further investigation. Finally, one may conduct a multi-methodological research (Choi et al. 2016b) on QR supply chain systems with real data analyses. This provides further insights into the real world applicability of QR and some probable extensions of the analytical model.

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A.1 Appendix: All Proofs

Proof of Lemma 2.1. (a) By directly comparing between the cases of QR and SR, the demand uncertainty under QR (with n-observation based information updating) is always smaller than the demand uncertainty under SR. By differentiation, we can find that $d_1(n)$ is decreasing in n, which implies the demand uncertainty reduction $((d_0+\delta)-(d_1(n)+\delta))$ is increasing in n. (b) When $n \to \infty$, $\lim_{n\to\infty} d_1(n) = \frac{d_0\delta}{nd_0+\delta} = 0$ and hence the demand uncertainty under QR $(d_1(n)+\delta)$ becomes δ. (Q.E.D.)

Proof of Lemma 3.1. (a) First of all, from (14.8), we have $EVQR_{SC}(n) = \left(\sqrt{d_0+\delta} - \sqrt{d_1(n)+\delta}\right) T_{SC}(s_{SC})$. From (14.3), we have:

$$T_{SC}(s_{SC}) = (p-v)\,\Phi^{-1}(s_{SC}) + (r-v)\,\Psi\left[\Phi^{-1}(s_{SC})\right]$$
$$= (p-v)\,\Phi^{-1}(s_{SC}) + (p-v)\,\Psi\left[\Phi^{-1}(s_{SC})\right] + (r-p)\,\Psi\left[\Phi^{-1}(s_{SC})\right]. \quad (14.30)$$

At Time 0, since the expected product leftover by the end of the season can be expressed as $\sqrt{d_0+\delta}\left\{\Phi^{-1}(s_{SC}) + \Psi\left[\Phi^{-1}(s_{SC})\right]\right\}$, which must be non-zero in the model we considered in this paper, we thus have:

$$\left[\Phi^{-1}(s_{SC}) + \Psi\left[\Phi^{-1}(s_{SC})\right]\right] \geq 0. \quad (14.31)$$

Put (14.31) into (14.30) implies that $T_{SC}(s_{SC}) > 0$. Since $\left(\sqrt{d_0+\delta} - \sqrt{d_1(n)+\delta}\right) > 0$, from (14.31), we have: $EVQR_{SC}(n) = \left(\sqrt{d_0+\delta} - \sqrt{d_1(n)+\delta}\right) T_{SC}(s_{SC}) > 0$.

(b) Differentiate $EVQR_{SC}(n) = \left(\sqrt{d_0 + \delta} - \sqrt{d_1(n) + \delta}\right) T_{SC}(s_{SC})$ with respect to n reveals that $dEVQR_{SC}(n)/dn > 0$.

(c) When $n \to \infty$, from Lemma 2.1, we have: $d_1(n) = 0$, and hence $EVQR_{SC}(n \to \infty) = \left(\sqrt{d_0 + \delta} - \sqrt{\delta}\right) T_{SC}(s_{SC})$. (Q.E.D.)

Proof of Lemma 4.1. Similar to the Proof of Lemma 3.1. (Q.E.D.)

Proof of Lemma 4.2. Notice that $\Phi^{-1}(s_R) < 0$ if and only if $s_R < 0.5$ and $\Phi^{-1}(s_R) \geq 0$ if and only if $s_R \geq 0.5$. Then, Lemma 4.2 can be proven by following the same approach as in the proofs of Lemmas 3.1 and 4.1. (Q.E.D.)

Proof of Lemma 4.3. When $c > p$, by direct observations from the analytical expressions, we have: $q_{0,R*} < q_{0,SC*}$ and $q_{1,R*}|\mu_1(n) < q_{1,SC*}|\mu_1(n)$. (Q.E.D.)

Proof of Lemma 5.1. (a) By equating $q^{\Omega}_{1,R*}\big|\mu_1(n)$ and $q_{1,SC*}|\mu_1(n)$, we know that $q^{\Omega}_{1,R*}\big|\mu_1(n) = q_{1,SC*}|\mu_1(n)$ if and only if $\widehat{m} = m*$. (b) Checking the first order derivative reveals that $EVQR^{\Omega}_{R}(n|\widehat{m} = m*)$ is a decreasing function of $\widehat{c}$, and $EVQR^{\Omega}_{S}(n|\widehat{m} = m*)$ is an increasing function of $\widehat{c}$. (Q.E.D.)

Proof of Lemma 5.2. Directly implied by using Lemma 5.1. (Q.E.D.)

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