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by
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ABSTRACT

Discount, Coupon, or Both? An Empirical Data-Based Analysis for Online Garment Retailers' Optimal Promotion Strategies

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Master of Philosophy

We investigate an online retailer's optimal strategies for her promotion of the garments that are classified based on their price levels and life cycle stages. Accordingly we consider nine scenarios. For each scenario, the retailer implements a promotion strategy that involves only a discount, only a coupon, or both of them. We develop a three-stage approach, in which we first perform regression analysis to identify the significant variables, then obtain the optimal decisions, and find the best scenario for the retailer. In general, the promotion with a discount depth is optimal for the garments at the introduction and decline stages, whereas that with a coupon is optimal for the garments at the maturity stage. Sales promotions for new garments cannot help to arouse potential customers' interests, whereas those for mature garments can significantly improve the reading rate. The most profitable garments are the high-priced garments at the introduction stage; but, the best sales garments are the low-priced garments at the maturity stage. The spring season is the best one for the retailer to promote the high-priced garments and the garments at the decline stage, the summer and autumn seasons are the best for a few scenarios, and the winter is a slack season for any promotion. The garments at the introduction and maturity stages may have a higher conversion rate on holidays. Any time limit in sales promotions influences customers' interests but may not affect their purchase intentions.

Key words: promotion; discount; coupon; reading rate; conversion rate.

DECLARATION

I declare that this is an original work based primarily on my own research, and I warrant that all citations of previous research, published or unpublished, have been duly acknowledged.

SIGNED

LIU Yang

CERTIFICATE OF APPROVAL OF THESIS

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1 Introduction

As the Internet technology rapidly advances, online shopping has become an increasingly important channel for customers to buy a variety of products. In the 2017 "double eleven" (i.e., November 11, 2017) global shopping festival in China, the sales at the Tmall (a primary online shopping platform in China) amount to 168.2 billion yuan in a single day, which breaks the sales record of 120.8 billion yuan achieved in 2016. In the American market, there is also a considerable development of online retailing. As indicated by an online consumption survey conducted by the Adobe Analytics, in the year of 2017, the American customers have spent \$19.62 billion on their online purchases during a five-day period from the Thanksgiving day (i.e., November 23, 2017) to the Cyber Monday (i.e., November 27, 2017). This purchase amount exceeds that in the same period of 2016 by \$2.6 billion, which represents a 15 percent increment. Moreover, according to the statistical data published by the National Retail Federation, the total amount of online retailing revenue in the U.S. in 2016 reaches \$655.8 billion, showing a 3.6% increase compared to that in 2015.

The rapid development of online shopping is also ascribed to retailers' considerable efforts on sales promotions, which are marketing activities that entice customers to buy, usually designed to yield an immediate sales effect. The promotions account for a large and growing part of firms' marketing budgets and act as a key instrument for retailers to stimulate sales and increase market share (Hardesty and Bearden 2003; Zhang and Wedel 2009). Van Heerde and Neslin (2017) showed that during the period from 1997 to 2011, sales promotions constitute roughly 75% of marketing expenditures for the US packaged goods manufacturers; and the other 25% is for advertising. There are a number of promotion strategies for online retailers, among which the price discount and the coupon are two most common ones, according to our literature review in Section 2. Wallace (2017) has interviewed some successful online business operators, and found that in practice, online retailers usually take advantage of the discount and the coupon to attract potential customers and maintain their loyalty. Although the two promotion strategies have been used by offline retailers for a long time, a proper use of them in online retail operations is important to stimulating the sales and is thus worth investigating. For example, as Nerd (2017) released in a survey, customers who redeem coupons in their consumptions generally spend 24% more than regular buyers. According to The Mood Media's report (2017), 54% of the U.S. customers had acknowledged that any promotion with a discount could drive them to make an impulse consumption.

The discount and the coupon differ in their availability to customers. Specifically, a discount is immediately available for all the customers who fulfill the basic conditions set by the retailer, whereas a coupon requires the customers who obtain coupons by various means to provide a unique coupon code during the checkout process. Since the retail price is a critical factor in influencing customers' purchase intentions, a discount of the price is a natural, direct strategy for retailers to drive sales and attract new customers. Nevertheless, some studies in the U.S. have revealed that compared to the price discount, the coupon has some distinct advantages. For example, the coupon strategy can help avoid customers' doubts on product quality, maintain the reference price of product in customers' mindsets, and refrain from misleading customers to perceive a lasting promotion time for price reduction. In particular, the promotion with a post-used coupon can improve the loyalty of existing customers, especially those with a higher price sensitivity. Compared to the traditional coupon, which customers can obtain in advance and use it in their current purchases, the post-used coupon is more effective in stimulating customers' repeated purchases. Since both the price discount and the coupon are common and also helpful in online promotions, it is interesting to investigate the question of when an online retailer should use only a discount, only a coupon, or both in her optimal promotion strategy.

There are many factors that affect the impact of a promotion strategy on online retailers' performance. Among these factors, the two inherent attributes of a product—i.e., product life cycle (usually including a product's three stages: introduction, maturity, and decline) and price level (usually including three price levels: low, medium, and high)—play a significantly important role when an online retailer design an effective promotion strategy. For example, for new products (i.e., those at the introduction stage), a coupon strategy may attract more customers to show their interests in sales promotions and may thus boost the product visibility in the market. For some outdated products (i.e., those at the decline stage), which occupy a storage place but make a small contribution to the total profit, sales promotion with a price discount may be effective in accelerating the clearance process and leaving space for more profitable products. Besides the two three-dimensional factors, other factors that significantly affect the retailer include gender, brand, holiday, time limit, and seasonality. These elements are important for the retailer to propose an optimal promotion strategy. For example, on the one hand, although holidays are critical times for online marketing, a collaboration between Bain and Earnest Research suggests that the customers attracted on holidays are not as profitable as those served on regular days. On the other hand, many retailers, e.g., Amazon, claim that they can achieve considerable sales on holidays steadily even when the economy is in recession (Cheris, Rigby and Tager 2017). In fact, our analysis with these factors significantly distinguish this thesis from extant publications, in addition to our study on the optimal promotion strategies in the nine scenarios regarding the garments at different life cycles and different price levels.

In Section 2, our review indicates that a large number of extant publications presented their experimental studies to examine the effectiveness of different promotion strategies. Although many publications applied quantitative methods to investigate the promotion-related issues, most of them were only focused on the effect of the promotions on the sales. This thesis is different from extant publications, as we mainly aim to find the optimal promotion strategies for online retailers in different settings. Specifically, our research questions are as follows:

1. How should the online retailer design promotion scheme tailoring to different types of product?

2. How should the online retailer identify the most profitable products subjected to various situations?

3. Given the profit are maximum, which type of product can gain popularity to the utmost extent? Under the same condition, which type of product should be chosen if the online retailer wants to boost the sales volume?

We propose a three-stage approach to find the optimal promotion strategy with empirical data. In the first stage, we first develop an aggregate regression model to identify the decision variables (i.e., the discount depth and the coupon value) and other independent variables that significantly influence the reading rate (i.e., the percentage of the customers who read promotion messages) and the conversion rate (i.e., the percentage of the customers who browse promotion details and also buy the product) in the retailer's promotions. This analysis helps us find the most suitable promotion strategy for each scenario. Then, using the significant variables, we construct a reading rate function and a conversion rate function, which are then used to build the retailer's profit. In the second stage, for each scenario, we maximize the retailer's profit to find her optimal decisions, to wit, the optimal discount depth and/or coupon value. In the third stage, we compare the optimal results in the nine scenarios to identify the best scenario with respect to the highest profit, the highest reading and conversion rates, or the highest sales. Moreover, we perform sensitivity analysis to expose the effects of some variables on the retailer's optimal promotion decisions and her performance in terms of the reading and conversion rates, the sales as well as her profit.

To apply the three-stage approach on the real world, we collect a three-year promotion dataset from an online Chinese garment retail company who operates her online business at the QQ social media platform. Based on two three-dimensional attributes (namely product life cycle and price level), we divide all the garments into nine categories each corresponding to a scenario.

The remainder of this thesis is organized as follows. In Section 3, we provide preliminaries including a description of the promotion strategies, an introduction to customers' purchase decisions, and a summary of a three-stage approach that used by the online retailer to find her optimal promotion strategies. We present our regression analysis in Section 4, which corresponds to our analysis in the first stage. In Section 5, we find the optimal promotion decisions for each scenario, which corresponds to the second stage; and also identify the best scenario for the retailer and perform sensitivity analysis to explore the influence of independent variables on the retailer, which corresponds to the third stage. In Section 6, we summarize our major findings, discuss the limitations in this thesis, and present some future research directions.

2 Literature Review

Recent years have witnessed a slow world economic growth, an increasing market fragmentation, a rampant brand proliferation, and an intense competition for market share. Firms have to absorb a high cost and also take many factors into consideration for their market promotions. It is thus a significant challenge for a firm to achieve the effectiveness of its market promotion (Ledingham, Kovac, Heric and Montaville 2013). In fact, today's firms are using a wide array of promotion tactics offline and online, and a large firm with numerous product lines and brands may have hundreds or thousands of promotion programs for various purposes and consumer segments. Recent industry reports, however, suggest that despite an increasing volume of promotions, many programs are not effective, or even have a negative effect[1]. A majority of the promotional designs evolve from the past, without the knowledge or assurance of their effectiveness. Improving promotional effectiveness and efficiency have been topics of considerable interest and research effort for decades.

Grewal et al. (2010, 2011) summarized the findings of both quantitative research and behavioral studies on how customers value and respond to sales promotions in various situations. Quantitative research has often been focused on the customer-packaged goods industry, where rich data covering long periods and across product categories are available (see, e.g., Ailawadi and Neslin 1998, Zhang and Wedel 2009, Felgate et al. 2012 , Howell, Lee, and Allenby 2016; Liu, Liu, and Chintagunta 2017, and Trivedi, Gauri, and Ma 2017). Most behavioral researches used experiments to manipulate various elements of promotional designs to isolate their effects (see, e.g., Darke and Chung 2005, Palazon and Delgado-Ballester 2009, Barone and Roy 2010, and Foubert and Gijsbrechts 2016).

When managers devise their promotion strategies, they need to address many questions, which include, but are not limited to, what incentives they would offer to customers, which type of customers they would aim to serve with effective promotional strategies, and when they would launch their promotion plans. In this thesis, we expect to explore the effective strategies that could help online retailers promote various products. Next, we review relevant publications, which are concerned with promotion effectiveness, promotion devising, and product classification.

2.1 Promotion Effectiveness

There are a large number of publications that study the effectiveness of promotions. Park and Lennon (2009) provided evidences to show that, in the online

[1]`https://www.bcg.com/publications/2015/retail-pricing-how-retailers-can-improve-promotion-effectiveness.aspx` (URL last accessed June 3, 2019).

apparel retailing context, the price promotion is a critical factor in influencing customers' perceived value which plays an important role in customers' purchase decisions. Gupta and Cooper (1992) mentioned that the appearance of the original price and the discounted price at the same time can apparently indicate customers' cost savings, thereby increasing customers' purchase intentions. Aydinli, Bertini, and Lambrecht (2014) classified the factors that influence the customer purchases into two streams, i.e., "affective factors" and "deliberative factors." Performing experiments with real field data, they elaborated that the price promotion can weaken customers' deliberation on purchase decisions. For this case, customers tend to make quicker decisions and to choose merchandises that are richer in emotion than the case when they are facing the original price with no promotion. Li et al. (2017) demonstrated that the weather condition is a critical factor in affecting customers' responses to mobile promotions. They found that, compared to the cloudy weather, the sunny weather results in higher and faster responses to mobile promotions, whereas the rainy weather has opposite effects, leading to lower and slower responses.

Existing studies have found that the effects of individual promotion attributes on sales are ambiguous and inconsistent across different settings (Ailawadi and Neslin 1998, Lemon and Nowlis 2002, and Grewal et al. 2011). Take featured promotions (store fryer) and price discount as an example. Lemon and Nowlis (2002) found that high-tier brands benefit more than low-tier brands from price promotions, displays, or feature advertising, but this advantage disappears when certain promotion tools are used in combination with one another. According to the findings by Ailawadi et al. (2006), a deep discount combined with featured promotions on high "consumer-pull" brands can generate high overall sales but result in lower profits. More recently, Gauri et al. (2017) showed that the featured promotions can build store traffic, especially when the categories being featured are the high penetration and high frequency. They also found that the promotions of branded items are more effective than the promotions of unbranded items. Moreover, a few studies have considered the effects of the threshold values of promotional attributes in assessing their effectiveness. Hardesty and Bearden (2003) proved that the price discounts are preferred over bonus packs when the high benefit levels are employed. Van Heerde, Leaflang, and Wittink (2001) examined the response of sales to the percentage of price discount and found that the feature advertising can increase the sales as a result of a discount of up to 20%, whereas the display can achieve higher sales from the discounts in excess of 20%. However, the systematic research is still lack in understanding the complexities of the potential synergy or interference among multiple promotion attributes at various threshold levels, as argued by Ailawadi et al. (2009) and Grewal et al. (2011).

Since a promotion strategy may perform differently under various conditions, it is important for retailers to consider many factors as possible in designing a promotion scheme.

2.2 Promotion Devising

Sismeiro and Bucklin (2004) used a sequence of binary probits to model and predict customers' purchases in online car retailings, with an aim to optimize the effect of promotions. Instead of using an one-step approach, they employed a conditional modeling approach to construct sequential decisions that customers need to make before their online purchases. The authors showed that the proposed approach in their paper possesses a high prediction accuracy and a great capability of identifying potential customers. Mehta and Ma (2012) developed a multicategory model to tackle the retailers' questions about how the retailer can allocate the promotion budget and arrange the promotional timing across multiple categories of customer packaged goods. They revealed that, as for customer packaged goods, ignoring the cross-category effects on customers' purchase decisions (incidence, quantity, and brand choice) might lead to opposite guidelines for retailers' allocation and timing decisions. Liu-Thompkins and Tam (2013) conducted three studies to differentiate repurchase customers according to their attitudinal royalties and habits. They offered different designs of cross-selling promotions catering to two kinds of repurchase customers, in order to eliminate the possible detrimental effects of ignoring their differences and to maximize the effectiveness of promotions.

By means of experimental studies, Cheng and Cryder (2018) demonstrated that the promotional credit outperforms the standard discount by arousing customers' double mental discounting across several purchases. In their setting, customers can obtain coupons if they purchase the specific promoted products, and they can redeem the coupons in their next purchases. Cheng and Cryder (2018) reported from their field experiments that the strategy of providing a promotion credit can enable customers to perceive the savings resulting from the promotion several times. To the best of our knowledge, most of the extant publications investigate an individual promotion strategy in the offline setting. Even though a few researchers have attempted to compare the effects of different promotion strategies and identify the best strategy, none of them have investigated the optimal promotion strategy when a retailer offers two or more promotions simultaneously in the online setting.

2.3 Product Classification

There are many factors that impose a significant influence on the performance of a product in several dimensions, i.e., the sales of the product, the profit of the firm which sells the product, and others. According to our review, we identify two important product attributes, which have an non-neglectable influence on the retail operations. The first is the "product life cycle" (PLC). Rink and Swan (1979) summarized 12 different patterns of PLC curves that had been recognized in literature. They concluded that the PLC is a critical factor to the product management. Thietart and Vivas (1984) showed that the effective strategies are usually a function of the PLC and other business features, which help provide a guidance for managers. They also proved that the PLC plays different but important roles in reality for various performance measurements. Wong and Ellis (2007) discovered in their empirical study that the link between market orientation and firm performance is the tightest in the growth stage and the loosest in the introduction stage of PLC. Madhani (2011) summarized the managerial implications from various aspects for each stage of PLC, including promotional strategies (i.e., pricing, advertising, etc.), sales force, etc. The second product attribute is the "price level" (PL). A stream of literature proposed that the product price can be classified into three levels, i.e., low, medium, and high (Lambert 1972, Rink and Swan 1979). Lambert (1972) testified the feasibility of the price classification method in an experimental study.

From the above review, we can conclude that many researchers have studied the differences among products that are located in different stages of PLC or PL. However, very few have jointly considered these two product attributes in their studies. It thus behooves us to understand the complexities of the potential synergy or interference among the promotion attributes (i.e., PLC and PL) and determine an optimal promotion scheme that can maximize the retailer's profit.

3 Preliminaries: Promotion Strategies, Customers' Purchase Decisions, and an Online Retailer's Decision-Making Stages

We consider an online retailer who chooses an optimal strategy to promote her product in a market. We first discuss the common promotion strategies that have been widely used by online retailers in practice, and specify our major research questions that have not been addressed in literature. Our analysis of such research questions illuminates the importance of this thesis. Then, we describe a customer's purchase decision process in which the customer receives the retailer's promotion message and decides on whether to buy or not. Using the empirical data from an online retailer, we identify three promotion strategies that can apply to nine scenarios. For our study, we propose a three-stage framework. In stages 1 and 2, for each scenario, we perform regression analysis on relevant empirical data to identify the influential promotion strategy, construct the retailer's profit function, and obtain the retailer's optimal decisions. In stage 3, we compare the retailer's maximum profits in all scenarios, and find the optimal scenario in which the retailer can obtain the highest profit.

3.1 The Common Promotion Strategies and Major Research Questions

In practice, the two promotional strategies commonly used by online retail operations are price discount and coupon. When a retailer discounts the original price of a product (which is denoted by p, and is usually recommended by the product manufacturer or the brand and tagged at the retailer's online shopping platform), her customers only need to pay a proportion of the original price. For the strategy, the retailer needs to determine a discount depth $\alpha \in [0, 1)$, which can be used to calculate each customer's payment as $(1 - \alpha)p$. The strategy of coupon includes the contents in two dimensions (i.e., timing and form). In the "timing" dimension, the retailer can choose either an in-used or a post-used approach. When the retailer adopts the former approach for a promotion, she should distribute her coupon offers (mostly, in the form of online coupon codes) to potential customers through some possible online channels such as advertising emails, web banner advertising, and mobile messages. Then, the customers who obtain the coupons can redeem them when they buy the promotional product from the retailer. When the retailer adopts the post-used approach, the customers can receive the coupons at the moment when they buy the promotional product, and can redeem the coupons only in their next purchases. In the "form" dimension, the retailer should specify a method of computing an amount awarded to each customer who redeems his or her coupon. The common methods contain the "dollar term" (i.e., a certain amount, denoted by $\beta \geq 0$, is deducted from the original price) and "percentage term" (i.e., an amount is computed as a constant proportion of the original price, similar to the price discount strategy).

According to the above discussion, we find that since the retailer may consider any one or both of the discount and the coupon strategies, there are three possible promotion strategies: (i) discount only strategy (in which the retailer determines a discount depth α), (ii) coupon only strategy (in which the retailer determines a coupon value β or a percentage), and (iii) the mixed strategy (in which the retailer make decisions for both the discount and the coupon). In order to find the optimal promotion strategy for the online retailer in a realistic manner, we obtain a field data from a leading online garment retailing company in China, who is anonymous for confidentiality reasons. Specifically, we collect the firm's empirical data regarding her promotions at the QQ social media platform (a popular online instant messaging software service developed by Tencent; see `http://www.imqq.com/English1033.html`). We learn from the data that in all the promotions, the firm only considered the price discount strategy and/or the dollar-term, post-used coupon strategy (which is hereafter simply called the "coupon" strategy). Accordingly, in this thesis we only focus on the retailer's promotion programs including a price discount and/or a coupon.

We investigate the impact of the retailer's price discount and coupon strategies on her sales volume and profit. We note from the empirical data that the retailer implements her promotion strategy for a variety of scenarios, which can be classified in terms of product life cycles and price levels. The product life cycle includes the following three stages: introduction, maturity, and decline; and the price level consists of the following three categories: low price level, medium price level, and high price level. Combining the product life cycles and price levels, we mainly consider nine scenarios as shown by Table 1, which include (i) introduction-low price level, (ii) introduction-medium price level, (iii) introduction-high price level, (iv) maturity-low price level, (v) maturity-medium price level, (vi) maturity-high price level, (vii) decline-low price level, (viii) decline-medium price level, and (ix) decline-high price level.

		Product Life Cycle		
		Introduction	**Maturity**	**Decline**
Price Level	**Low**	(i)	(iv)	(vii)
	Medium	(ii)	(v)	(viii)
	High	(iii)	(vi)	(ix)

Table 1: The nine scenarios as a result of combining the product life cycles and price levels

It is important to examine which promotion strategy is optimal in each scenario, because our results would help practitioners choose their proper online promotion strategies. For example, one may raise some natural—and interesting—questions as follows: when an online retailer plans to promote a high price level (luxury) product when the product is newly introduced into the market, should the retailer adopt a price discount strategy, a coupon strategy, or a mixture of them? If the product at a low price level is at the decline stage of its life cycle, what promotion strategy should be considered by the retailer? A number of similar questions arising from different mixtures of product life cycles and price levels are worth addressing. In addition, assuming that the retailer uses her optimal promotion strategy for each of nine scenarios, we also need to investigate in which scenario the retailer can achieve the highest profit. To address the question, we should compare the retailer's maximum profits in the nine scenarios and find the most profitable scenario for the retailer. As our review in Section 2 indicates, our major research questions regarding the optimal promotion strategy for each scenario and the most profitable scenario have not been addressed in extant publications. We expect that our results for these questions are of great help to online retailers in effectively promoting their products online.

3.2 Customers' Purchase Decision Processes under a Promotion Program

We now discuss customers' purchase decision processes when the retailer offers a promotion program. The retailer serves a number of fans or members who have followed the retailer at an online platform or have agreed to receive the retailer's promotion messages by, e.g., emails and mobile messages. These fans or members are the retailer's potential customers. We use n to denote the number of the retailer's potential customers. Each potential customer needs to experience two steps in his or her purchase decision process (from receiving promotion messages to making a purchase decision). Next, we specify the two steps.

In the first step, all the potential customers receive a promotion message sent by the retailer. As usual, the promotion message consists of both a short description of the promotional product and a hyperlink towards an online transaction website with more details about the product. The potential customers should decide on whether to click on the hyperlink in the message for specific information or not. If the message cannot arouse the customers' interests, then they may not read it but instead remove it directly. Otherwise, the customers may click the hyperlink and go to a relevant website for the specific promotion information. Therefore, in the first step, we need to examine how many potential customers click the hyperlink after reading the retailer's promotion message. This implies the likelihood of customers' purchases, because more reads would by and large result in a larger number of purchases. It is thus necessary for us to consider the *reading rate* of potential customers for a promotion program, which is denoted by R_r and can be computed as the ratio of the number of potential customers clicking the hyperlink to access the specific promotion information to the number of potential customers who receive a message for the promotion (i.e., n).

In the second step, the customers who have clicked the promotion hyperlink and browsed a relevant website should make a decision on whether to buy the product or not. Noting that each customer does not necessarily buy if the product and the promotion are not sufficiently attractive, we need to compute the ratio of the number of potential customers who decide to buy the product to the number of potential customers clicking the hyperlink to access the promotion information, which is defined as *conversion rate* R_c.

3.3 A Three-Stage Approach for the Analysis of the Retailer's Promotion Strategies

We describe a three-stage framework for our analysis, which can help obtain the retailer's influential promotion strategy in each scenario, find the optimal design of promotion strategy in each scenario, and identify the most profitable scenario for the retailer.

3.3.1 Stage 1: Regression Analysis with Empirical Data

For the nine scenarios listed in Table 1, we use the empirical data to conduct two aggregated regression analyses and obtain the functions characterizing the significant effects of the firm's decisions (e.g., price discount depth α and coupon value β) and other major independent variables (i.e., original price, seasonality, etc.) on reading rate R_r and conversion rate R_c in customers' decision processes. That is, for each scenario, we find two regression functions to express R_r and R_c in terms of α, β, and other significant factors. Our regression analysis may expose the insignificant influence of α and β on R_r and/or R_c, which addresses the question of which promotion strategy is the most suitable in each scenario. For example, for a scenario, if α plays an insignificant role in both R_r and R_c but β significantly influences the two rates, then we can view the promotion strategy with only the coupon as the most suitable one for the scenario, and then find the corresponding regression functions only in terms of β.

3.3.2 Stage 2: Optimal Promotion Decision(s) for the Most Suitable Promotion Strategy in Each Scenario

Under the most suitable promotion program for a scenario, the retailer needs to determine the values of discount depth $\alpha \in [0, 1)$ and coupon value $\beta \geq 0$. As our empirical study in stage 1 indicates, the values of α and β could be zero, which means that the retailer may not offer price discount and/or dollar coupon in the program. For example, if we find in stage 1 that, for a scenario, the promotion program that significantly impacts reading and conversion rates is a mixed (discount-coupon) one, then in the program, $\alpha > 0$ and $\beta > 0$. But, if the most suitable program for a scenario is the one in which only the price discount has a significant influence, then $\alpha > 0$ and $\beta = 0$.

In stage 2, we aim to obtain the retailer's optimal discount and/or coupon decisions that maximize the retailer's profit under the most suitable promotion program in each scenario. As operated by the firm who provides the empirical data, the retailer promotes only one product in each promotion program. Therefore, for a given scenario, the retailer's profit $\pi(\alpha, \beta)$ is the profit margin (i.e., $m(\alpha, \beta)$) times the total sales volume of the product (i.e., $s(\alpha, \beta)$), i.e., $\pi(\alpha, \beta) = m(a, \beta) \times s(\alpha, \beta)$, in which the profit, the profit margin, and the total sales volume are all dependent on the retailer's decision variables α and β.

Letting p denote the original price of the product in each scenario, we find that without considering dollar coupons, the retailer can receive payment $p(1-\alpha)$ from each customer who buys the product. In addition to the discount, the retailer needs to determine the face value of the dollar coupon (i.e., β) if the coupon is also offered to customers. It is apparently required that β is in the range $[0, p(1-\alpha))$, because the coupon value should not exceed each customer's net expense for his or her purchase. In reality, each customer may or may not redeem the coupon; as usual, the coupons distributed by the retailer are partially redeemed by customers. Denoting by γ the average redemption rate of the coupons, we calculate the retailer's *expected* payment to each customer as $\gamma\beta$. Thereby, we obtain the retailer's unit profit $m(\alpha, \beta)$ as $m(\alpha, \beta) = p(1-\alpha) - \gamma\beta - c$, where c represents the retailer's unit acquisition cost of the product.

We learn from Section 3.2 that a proportion R_r of n potential customers read the retailer's promotion message and a proportion R_c of the customers who read the message buy from the retailer. Thus, when the retailer chooses the most suitable strategy for a scenario, we can calculate the sales volume as $s(\alpha, \beta) = n \times R_r \times R_c$. Therefore, for a given scenario, the retailer's profit is given by

$$\pi(\alpha, \beta) = m(a, \beta) \times s(\alpha, \beta) = n \times R_r \times R_c \times [p(1-\alpha) - \gamma\beta - c], \qquad (1)$$

where one or both of R_r and R_c could be the functions of α and β, according to our regression in stage 1; and c is the retailer's unit acquisition cost for the product. According to the practice of the firm who provides the empirical data, the original price is computed based on the unit acquisition cost and a markup percentage $\lambda \geq 0$; that is, $p = c(1+\lambda)$. We can thus rewrite the profit function in (1) as

$$\pi(\alpha, \beta) = n \times R_r \times R_c \times \{c[(1+\lambda)(1-\alpha) - 1] - \gamma\beta\}, \qquad (2)$$

Maximizing $\pi(\alpha, \beta)$ in (2) w.r.t. α and β, we can obtain the retailer's optimal decisions for the most suitable promotion strategy in each scenario.

3.3.3 Stage 3: Comparison Among Results in Different Scenarios and Sensitivity Analysis with Managerial Implications

We compare the retailer's maximum profits that are obtained for all scenarios in stage 2, and find the most profitable scenario in which the retailer can obtain her highest profit. In addition, we perform sensitivity analysis to examine the effect of some important parameters, as shown in our regression analysis in stage 1, including the unit acquisition cost, the markup percentage, and the other parameters (e.g., brand, holiday, time limit) that significantly influence the reading and conversion rates. Specifically, as the value of a parameter increases, we investigate how the optimal decisions for the most suitable promotion strategies change and whether the most profitable scenario alters or not. Our study in stage 3 is mainly motivated by the fact that in reality, the exogenous factors such as the economic and industry statuses and the customers' purchase and consumption preferences may change over time. The retailer may respond to different external situations by changing her optimal promotion strategy. We expect that our results in stage 3 can help the retailer recognize the influence of ever-changing, exogenous factors on her optimal strategy and performance.

4 The Regression Analysis with Empirical Data

For our regression analysis in stage 1 as described in Section 3.3.1, we use the empirical data collected from an online Chinese retailer, which was established in 2001 and is selling both casual and formal garments of diverse brands for all ages and genders. The retailer's online business is operated only at the QQ online social media platform, where around 100,000 fans have subscribed the promotion messages from the retailers. This means that the number of the retailer's potential customers is $n = 100,000$. Each year, this retailer launches considerable product promotion programs (which are observable to all of her potential customers) at the online platform. Specifically, each item of the promotion data contains many corresponding information including gender, brand, holiday, time limit, ect., which will be elaborated later. These characteristics of each promotion offer us an opportunity to measure the influence of other factors when we study the efficacy of different promotion strategies. We have obtained the empirical dataset that contains the mentioned details about 557 product promotions provided between January 2011 and December 2013, in which the sales of this retailer ranked in top ten among all Chinese online garments retail company.

4.1 The Description of the Variables in the Regression Analysis

In the dataset there are specific data about original price, price discount, coupon, time limit, gender, holiday, brand, and some performance measures such as reads, sales and comments. According to the dataset, we define the variables for our regression study, as given in Table 2.

We note from the empirical dataset that the retailer offers a price discount in each promotion program which may or may not include a coupon simultaneously. That is, under any promotion program run by the retailer, customers can enjoy a price discount α but may or may not receive a coupon with its face value β. Although, for each promotion program, the dataset explicitly provides a discount depth and a coupon value if the coupon exists in the program, we cannot find any information about unit acquisition cost c of each promoted product in the dataset. The value of c is necessary and also important, as we need it to compute the retailer's profit and find the optimal promotion strategy. We learn from the retailer that the markup percentages for the promoted products range from from 100% to 300% with the average value of 200%, i.e., $\lambda = 200\%$. Thus, using original price p and average markup percentage λ, we can estimate the unit acquisition cost as $c = p/(1 + \lambda) = p/3$, which means that for any product in this empirical

Variable	Notation	Description
Customer Size	n	The number of all potential customers; $n = 100,000$
Reading Rate	R_r	The ratio of the number of customers who read the promotion message after receiving it to the number of all potential customers
Conversion Rate	R_c	The ratio of the number of the customers who decide to buy to the number of the customers who read the promotion message
Cost	c	The unit acquisition cost of a promoted product
Original Price	p	The before-discounted price advised by the brand of a promoted product and tagged online
Discount Depth	α	The ratio of the discounted price to original price
Coupon Value	β	The coupon value in dollars for a promoted product
Redemption Rate	γ	The percentage of customers who redeem their coupons
Markup	λ	The average profit margin for the retailer (percentage)
Product Life Cycle	$LifeCycle$	The three stages/periods in a promoted product's life cycle, which includes "introduction" (code as 1), "maturity" (2), and "decline" (3)
Price Level	$PriceLevel$	The three price tiers for a promoted product, which include "low" (code as 1), "medium" (2), and "high" (3)
Time Limit	$TimeLimit$	A promotion is offered with a time restriction or not
Gender	$Gender$	The promoted product is for male or female
Brand	$Brand$	The promoted product is a domestic or foreign brand
Holiday	$Holiday$	The promotion is launched during a holiday or not
Seasonality	$Seasonality$	The season in which a promotion is released, we code winter as "1" if the promotion is in December, January, and February; code spring as "2" if it is in March, April, and May; code summer as "3" if it is in June, July, and August; and code autumn as "4" if it is in September, October, and November

Table 2: A list of major variables in our regression study

dataset, the retailer's unit acquisition cost is a third of her retail price on average.

The product life cycle (denoted by the variable "$LifeCycle$") is an important factor in our analysis, and we find from Table 2 that for any product, the life cycle includes the "introduction" stage, the "maturity" stage, and the "decline" stage. For each promotion, we code the life cycle attribute of the promoted product according to the theme of the promotion. Specifically, when a promotion program is launched, potential customers can receive a promotion message sent by the retailer, which indicates a theme of the promotion—i.e., a brief introduction about the promoted product—and a hyperlink towards an online transaction website. If the theme contains the characters including "new product recommendation," "launch event," and other similar characters, then we can recognize this promoted product as one at the introduction stage with code "1." For the promotion of any product at the maturity stage with code "2," the theme includes the characters such as "rewards for fans," "bestselling," "stylish," etc. Similarly, we recognize the product at the decline stage with code "3," if its theme has the characters "clearance sales," "rush," and others.

We classify all the promoted products according to their price levels, which is represented by variable "$PriceLevel$" as defined in Table 2. Our classification is based on the original price of each product. According to the empirical dataset, there are three price levels which are the "low" price level, the "medium" price level, and the "high" price level. We naturally define 250 yuan and 400 yuan as the upper bound of the range for the low price level and the lower bound of the range for the high price level, respectively. That is, any product with original price p in the range [0,250] (i.e., $p \in [0, 250)$) is at the low price level with code "1," one with $p \in [250, 400)$ is at the medium price level with code "2," and one with $p \in [400, +\infty)$ is at the high price level with code "3."

We mainly classify all products according to their two-dimensional statuses in the product life cycle and the price level, thereby investigating and comparing nine scenarios as shown in Table 1. In our regression study, in addition to the product life cycle and the price level, we examine whether other variables have a significant influence on the reading and conversion rates. One may learn from Table 1 that these variables include the time limit, the gender, the brand, the holiday, and seasonality, which are specified below.

1. The time limit, denoted by "$TimeLimit$," contains the information regarding whether the promotion have a time restriction or not. If the theme of a promotion indicates a clue about the time limit, e.g., "flash sale" and "within 72 hours," we consider the promotion as one with a time restriction and set $TimeLimit = 1$. Otherwise, if there is no evidence showing a time restriction, then $TimeLimit = 0$.

2. The gender variable "$Gender$" is a 0-1 one capturing the sex of the customers for whom the retailer's promoted product is designed. If the promoted product is designed for male persons, then we set $Gender = 0$; otherwise, $Gender = 1$.

3. The retailer sells the garments of different brands in the world. Dividing all products into two categories "domestic" and "foreign," we define a 0-1 variable "$Brand$," which assumes the value of 1 (i.e., $Brand = 1$), if a promoted product possesses a foreign brand; and assumes the value of 0 (i.e., $Brand = 0$), otherwise.

4. Since any holiday is a hot time for retailers to promote their products, we accordingly define a 0-1 variable "$Holiday$" to explore if the retailer's optimal strategies for the holiday promotions differ from those for the non-holiday promotions. We set $Holiday = 1$ for the promotions on holidays which include the Spring Festival, the Valentine's Day, the National Day, the Christmas, etc., and set $Holiday = 0$ for other promotions.

5. Each year consists of four seasons, which, as agreed by most persons, includes the winter (from December to February), the spring (from March to May), the summer (from June-August), and the autumn (from September to November). Observing that the retailer has launched her promotion programs in each of the four seasons in which she only sells seasonal garments, we define an ordinary variable "*Seasonality*" with a value of 1 (for "winter"), 2 (for "spring"), 3 (for "summer"), or 4 (for "autumn").

Using the firm's empirical data, we can obtain the descriptive statistics of the variables in our regression analysis, as given in Table 3, in which we winsorize continuous variables (i.e., R_r, R_c, α, β, and p) at the 1% and 99% levels to minimize the influence of outliers.

Variable	**Observations**	**Mean**	**S.D.**	**Min.**	**Max.**
R_r	557	0.076	0.045	0.020	0.282
R_c	557	0.009	0.007	0.000	0.039
α	557	0.723	0.120	0.238	0.920
β	557	127.871	145.060	0	500
p	557	346.995	186.431	99	1289
$LifeCycle$	557	1.928	0.633	1	3
$PriceLevel$	557	1.944	0.726	1	3
$TimeLimit$	557	0.379	0.486	0	1
$Brand$	557	0.899	0.301	0	1
$Gender$	557	0.921	0.270	0	1
$Holiday$	557	0.176	0.381	0	1
$Winter$	577	0.167	0.373	0	1
$Spring$	557	0.321	0.467	0	1
$Summer$	557	0.255	0.436	0	1
$Autumn$	557	0.257	0.437	0	1

Table 3: The descriptive statistics of the variables in our regression analysis

4.2 The Regression Analysis Results

We now perform a two-step regression analysis. In the first step, we recognize the promotion strategy (i.e., only a price discount, only a coupon, or a strategy of combining the discount and coupon) and the other variables (i.e., original price, time limit, gender, brand, holiday, and/or seasonality) that significantly influence the reading and conversion rates. In the second step, we construct a reading rate function and a conversion rate function that are both in terms of the significant independent variables as found in step 1.

4.2.1 The Independent Variables that Significantly Affect the Reading and Conversion Rates

Using the empirical data, we construct regression models to find the impactive promotion strategy and variables for nine scenarios, i.e., scenarios (i) to (ix) as defined in Table 1. As in practice, both discount depth α and coupon value β are likely to have a nonlinear rather than a simple and monotone, linear influence on reading rate R_r and conversion rate R_c. To model such nonlinear effects, we include quadratic terms of these two independent (and also decision) variables (i.e., α and β) in our regression functions. Due to the limited sample size, we cannot draw reliable results by running a separate regression for each scenario. Thus, in the regression analysis for each of the reading and conversion rates, we build a single, aggregate regression model to examine whether the promotion strategies (i.e., price discount and coupon) are significantly influential in all the nine scenarios. The regression analysis with an aggregate model has been discussed and used by a number of publications including Hocking (1976), Gelman and Hill (2006), Preacher, Curran, and Bauer (2006), etc.

Since the values of discount depth α and coupon value β as well as their quadratic terms are different in the nine scenarios, we define α_i and β_i ($i = 1, 2, \ldots, 9$) as the discount depth and coupon value in scenario i. For the values of other variables in our regressions, see Table 2. According to our discussion above, we develop the following aggregate regression models to examine the effect of the promotion strategies and other variables on R_j, where $j = r$ if R_j represents reading rate R_r, and $j = c$ if R_j refers to conversion rate R_c.

$$
\begin{aligned}
R_j \;\; = \;\; & a_0^j + \sum\nolimits_{i=1}^{9} (a_{1i}^j \times \alpha_i + a_{2i}^j \times \alpha_i^2 + a_{3i}^j \times \beta_i + a_{4i}^j \times \beta_i^2) \\
& + b_1^j \times Gender + b_2^j \times Brand + b_3^j \times p + b_4^j \times Holiday + b_5^j \times TimeLimit \\
& + b_6^j \times Spring + b_7^j \times Summer + b_8^j \times Autumn + \varepsilon_j, \qquad (3)
\end{aligned}
$$

where, for $j = r, c$, a_0^j is the base value independent of any independent variable; a_{ki}^j ($k = 1, 2, \ldots, 4$; $i = 1, 2, \ldots, 9$) denotes the parameters for the promotion variables and their quadratic terms; b_i^j ($i = 1, 2, \ldots, 8$) represents the parameters for the variables unrelated to the promotion; and ε_j is the error term of the regression. Our regression model in (3) does not involve the seasonality term "$Winter$," because this term is linearly dependent on other seasonality terms "$Spring$," "$Summer$," and "$Autumn$." The regression results with the retailer's empirical data are summarized in Table 4, from which we can identify the promotion strategies that significantly affect the reading and conversion rates for nine scenarios.

The Significant Effects of the Most Suitable Promotion Strategies on the Reading Rate We begin by discussing the significantly influential (the most suitable) promotion strategies for reading rate R_r. For each of the nine scenarios defined in Table 1, we use the regression results for α_i and β_i ($i = 1, 2, \ldots, 9$) to examine if only the discount depth, only the coupon, or both significantly influence the reading rate. We summarize our findings in Table 5.

We learn from Table 5 that the discount depth has a significant influence on reading rate R_r in scenario (iv), and the coupon value plays a significant role in affecting the reading rate in scenarios (v), (vi), and (viii). For the garments at the introduction stage of their product life cycles, neither the discount depth nor the coupon value has a significant correlation with the reading rate. That is, when a garment is first introduced into the market, whether to offer a promotion

Variables	R_r	R_c	Variables	R_r	R_c	Variables	R_r	R_c	Variables	R_r	R_c
α_1	0.0610 (0.159)	-0.0797*** (0.0259)	α_4	0.184 (0.118)	-0.0647*** (0.0191)	α_7	-0.125 (0.152)	-0.0515** (0.0246)	p	3.76e-05 (2.44e-05)	-1.12e-05*** (3.96e-06)
α_1^2	-0.0645 (0.182)	0.0880*** (0.0295)	α_4^2	-0.222** (0.104)	0.0633*** (0.0170)	α_7^2	0.187 (0.154)	0.0474* (0.0250)	$TimeLimit$	0.0115*** (0.00416)	0.00109 (0.000675)
β_1	-0.000144 (0.000229)	1.00e-05 (3.72e-05)	β_4	0.000117 (0.000139)	4.08e-05* (2.26e-05)	β_7	0.000574 (0.000390)	4.70e-05 (6.34e-05)	$Gender$	0.0284*** (0.00694)	-0.00409*** (0.00113)
β_1^2	8.88e-07 (6.96e-07)	-2.29e-08 (1.13e-07)	β_4^2	-7.73e-08 (5.25e-07)	-2.89e-09 (8.52e-08)	β_7^2	-2.97e-06 (1.91e-06)	-1.50e-07 (3.10e-07)	$Holiday$	-0.00603 (0.00536)	0.00170* (0.000871)
α_2	-0.0819 (0.137)	-0.0773*** (0.0223)	α_5	0.0217 (0.112)	-0.0483*** (0.0181)	α_8	0.119 (0.130)	-0.0432** (0.0212)	$Brand$	0.0235*** (0.00650)	0.00215** (0.00106)
α_2^2	0.124 (0.138)	0.0800*** (0.0224)	α_5^2	0.00784 (0.0958)	0.0405*** (0.0156)	α_8^2	-0.0523 (0.129)	0.0440** (0.0210)	$Spring$	0.0362*** (0.00633)	-0.00143 (0.00103)
β_2	0.000308 (0.000221)	1.21e-05 (3.59e-05)	β_5	0.000184** (8.79e-05)	1.10e-05 (1.43e-05)	β_8	-0.000400*** (0.000136)	-4.40e-05** (2.20e-05)	$Summer$	0.0310*** (0.00667)	0.000258 (0.00108)
β_2^2	-9.96e-07 (8.53e-07)	-5.19e-08 (1.39e-07)	β_5^2	-3.75e-07 (2.72e-07)	-2.56e-08 (4.41e-08)	β_8^2	9.13e-07*** (3.53e-07)	6.96e-08 (5.73e-08)	$Autumn$	0.0181*** (0.00622)	0.00136 (0.00101)
α_3	-0.0192 (0.145)	-0.0609*** (0.0235)	α_6	-0.0633 (0.113)	-0.0405** (0.0183)	α_9	0.0620 (0.201)	-0.0470 (0.0327)	α_0	-0.0350 (0.0357)	0.0253*** (0.00579)
α_3^2	0.0338 (0.155)	0.0617** (0.0252)	α_6^2	0.0739 (0.102)	0.0330** (0.0166)	α_9^2	-0.00784 (0.211)	0.0351 (0.0343)			
β_3	0.000248 (0.000181)	-2.44e-06 (2.94e-05)	β_6	0.000202*** (6.37e-05)	3.00e-06 (1.03e-05)	β_9	-8.03e-05 (0.000140)	2.06e-06 (2.27e-05)	**Observations** **Adjusted-R**	557 0.164	557 0.189
β_3^2	-5.53e-07 (4.70e-07)	3.36e-09 (7.63e-08)	β_6^2	-2.25e-07** (9.87e-08)	4.92e-09 (1.60e-08)	β_9^2	3.44e-08 (1.71e-07)	6.97e-09 (2.77e-08)			

Table 4: The regression results regarding the effects of the promotion variables (i.e., α_i and β_i, for $i = 1, 2, \ldots, 9$) and other independent variables (i.e., p, $TimeLimit$, $Gender$, $Holiday$, $Brand$, $Spring$, $Summer$, and $Autumn$) on reading rate R_r and conversion rate R_c. Note that "*" denotes significance at 10%; "**" denotes significance at 5%; and "***" denotes significance at 1%

		Product Life Cycle		
		Introduction	**Maturity**	**Decline**
Price Level	**Low**	(i): No strategy	(iv): Discount	(vii): No strategy
	Medium	(ii): No strategy	(v): Coupon	(viii): Coupon
	High	(iii): No strategy	(vi): Coupon	(ix): No strategy

Table 5: The promotion strategy that significantly impacts reading rate R_r in each of the nine scenarios

program or not cannot affect customers' purchase intentions for the new garment. However, for the garments at the maturity stage of their life cycles, the correlation between a promotion strategy and the reading rate becomes significant. More specifically, at the maturity stage, a promotion program only involving a price discount for a garment at the low price level can significantly arouse customers' interests in the garment. As a result, customers may intend to obtain further and detailed information about the product by clicking the hyperlink in the promotion message. For a medium- or high-priced product at its maturity stage, a promotion with a coupon can also help stimulate customers' interests of reading the promotion message sent by the retailer. However, for the garments at the decline stage, a coupon promotion can significantly influence the reading rates for the medium-priced garments, and no strategy can significantly affect customers' interests in the promotions for the low- and high-priced garments.

We summarize our findings as in the following remark.

Remark 1 For an online retailer, any discount or coupon strategy may not significantly affect customers' intentions to read the retailer's message of promoting a garment at the introduction stage of its life cycle. However, a discount or coupon strategy is of significant help to influencing customers' interests in any promotion for a garment at the maturity stage. The discount depth is significant for the low-priced garments, whereas the coupon value is significant for the medium- and high-priced garments. For the garments at the decline stage, the coupon strategy is significantly effective in arousing customers' attentions to any promotion for a medium-priced garment; but, no strategy is significant for the low- and high-pricing garments.

We conclude from our aggregate analysis that, in general, the coupon value plays a more significant role than the discount depth in affecting the reading rate of customers. ■

The Significant Effects of the Most Suitable Promotion Strategies on the Conversion Rate We present Table 6 to show the most suitable promotion strategies that can significantly affect conversion rate R_c for each of the nine scenarios. One can apparently learn from Table 6 that discount depth α possesses a significant correlation with the conversion rate in all the scenarios except for scenario (ix). However, the coupon value β only significantly impacts the conversion rate for scenarios (iv) and (viii) for which the discount depth is also significant. Our result reveals that the discount depth is more effective than the coupon value in influencing customers' purchase intentions. That is, an instant price deduction can lead to a stronger effect on customers' purchases and thus the retailer's sales vis-à-vis a post-used coupon. Moreover, our findings in Table 6 suggest that for some scenarios such as (iv) and (viii), the retailer could jointly use the discount strategy and the coupon strategy with an aim to prevent customers from abandoning their shopping carts. Although a pure or mixed promotion strategy significantly influences customers' purchases in most scenarios, for scenario (ix) both the discount and the coupon strategies do not have a significant correlation with the conversion rate. That is, for the high-priced garments at their decline stages, it may not be useful to offer a promotion program for increasing the conversion rate.

Remark 2 The discount depth is a promotion strategy that significantly influences customers' purchase intentions for all the garments except for those with a high price at the decline stage. But, the coupon value is only significant for the

		Product Life Cycle		
		Introduction	**Maturity**	**Decline**
Price Level	**Low**	(i): Discount	(iv): Both strategies	(vii): Discount
	Medium	(ii): Discount	(v): Discount	(viii): Both strategies
	High	(iii): Discount	(vi): Discount	(ix): No strategy

Table 6: The promotion strategy that significantly impacts conversion rate R_c in each of the nine scenarios

low-price garments at the maturity stage and the medium-priced garments at the decline stage, in addition to the significant effects of the discount depth. Nevertheless, neither the discount nor the coupon can significantly alter customers' intentions to buy the high-priced products at their decline stages.

We conclude that the discount strategy is more effective than the coupon strategy in affecting the percentage of the customers who read the message and decide to buy. This is different from our findings for the reading rate as in Remark 1 in that the discount is a more effective strategy for the conversion rate whereas the coupon strategy is more significant for the reading rate. ■

The Effects of Other Variables on the Reading and Conversion Rates

We examine the effect of other variables that are not related to promotion strategies on both reading rate R_r and conversion rate R_c. We find from Table 4 that, among these variables, *Gender* and *Brand* are significantly correlated with both R_r and R_c. Specifically, the male and female customers have significantly different performances when they decide on whether to browse the promotion website by clicking the hyperlink within the promotion message or not, and also act differently when they make a decision on whether to buy the promoted garment after reading the promotion details or not. This result implies that when the retailer makes her promotion strategy, she need to consider the gender of the potential customers for whom a promoted garment is designed. In addition, the brand of a promoted garment plays a significant role in both the reading rate and the conversion rate. That is, the customers' responses to the retailer's promotions for the garments of domestic or foreign brands are different. The retailer should take the garment brand into consideration when she determines a promotion strategy. The above findings indicate that the two dummy variables $Gender$ and $Brand$ in our regression significantly influence the reading and conversion rates in a promotion program and thus, they should serve as two important factors in the retailer's promotion decision.

Different from variables $Gender$ and $Brand$, any other variable only has a significant correlation with either R_r or R_c. Variables $TimeLimit$, $Spring$, $Summer$, and $Autumn$ only have a significant influence on R_r, whereas p and $Holiday$ only significantly influence R_c. As shown by our results, when a potential customer receives a promotion message, he or she pays considerable attention to whether the retailer imposes a time restriction for the promotion or not ($TimeLimit$). The promotion with a time restriction may significantly reduce potential customers' interests and may thus prevent them from reading the promotion details. In the case that a customer accepts the time restriction, the customer does not consider this issue in his or her purchase decision making. As a result, reading rate R_r significantly depend on variable $TimeLimit$, but conversion rate R_c does not rely on this variable in a significant manner.

Similar to the effect of $TimeLimit$ on potential customers' behaviors, the release time of a promotion in a year ($Seasonality$) also significantly affects the reading rate but does not significantly influence the conversion rate. This means that when customers receive a message for promoting a garment in a season, they may not miss the chance to buy the seasonal product and thus have an incentive to click the hyperlink within the message for details about the product prior to the end of the promotion. But, when a customer arrives at the purchase decision-making stage, the seasonality is no longer a key determinant, as the customer mainly considers some non-seasonality factors to decide on whether to buy or not. Hence, in different seasons, customers' reactions to promotion messages differ significantly in whether to browse the website for more information or not, whereas their purchase intentions have no significant difference.

Our regression results expose that some variables (i.e., original price p and holiday $Holiday$) are significantly correlated with customers' purchase decisions (i.e., the conversion rate) rather than their interests in the retailer's promotions (i.e., the reading rate). Intuitively, the price is a critical factor in influencing customers' purchase intentions after the customers browse the shopping website, as statistically reflected by the significant correlation between p and R_c in Table 4. However, the result reveals that the original price does not have a significant influence on customers' willingness to click the hyperlink for reading the promotion details. This may reveal a fact that the price, by and large, do not play any role before customers go to the purchase decision-making stage, which is consistent with our conclusion in Remark 1 that in general, the price discount cannot significantly arouse customers' interests in the retailer's promotion programs. Similar to the effects of price p, whether a promotion is launched on holiday or not has no significant correlation with R_r but is significantly correlated with R_c. That is, customers may not have any impulse to browse shopping websites on holidays; but, they have significantly different purchase intentions in comparison to the regular time.

4.2.2 The Reading Rate Function and the Conversion Rate Function

According to our regression analysis in step 1, as given in Section 4.2.1, we can identify the independent variables that are significant correlated with two dependent variables (i.e., R_r and R_c). Now, we go to step 2 in which we find the the reading rate function and the conversion rate function. For each function, we need to estimate the coefficients for the corresponding significant independent variables in each of the nine scenarios defined in Table 1. For instance, for scenario (iv) in which the retailer promotes a low-priced product at the maturity stage of its life cycle. We learn from Table 5 that discount depth α significantly influences reading rate R_r, and also find from Table 6 that both discount depth α and coupon value β significantly affect conversion rate R_c. Moreover, according to Table 4, we find that the promotion-unrelated variables significantly affecting R_r include *Gender*, *Brand*, *TimeLimit*, and *Seasonality*, and those significantly influencing R_c are *Gender*, *Brand*, p, and *Holiday*. Using the above, for scenario (iv), we can develop the functions for R_r and R_c in terms of the significant variables as

$$\begin{cases} R_r = & a_0 + a_1 \times \alpha^2 + b_1 \times Gender + b_2 \times Brand + b_3 \times TimeLimit \\ & +b_4 \times Spring + b_5 \times Summer + b_6 \times Autumn + \varepsilon, \\ R_c = & a_0 + a_1 \times \alpha + a_2 \times \alpha^2 + a_3 \times \beta + b_1 \times Gender + b_2 \times Brand \\ & +b_3 \times p + b_4 \times Holiday + \varepsilon. \end{cases} \quad (4)$$

Similarly, we can obtain the functions of R_r and R_c for the other eight scenarios. Our regression results for the estimated coefficients and standard errors in the nine scenarios are presented in Table 7.

Next, we interpret the results in Table 7 with regard to the effect of each independent variable on R_r and R_c. Noting from Section 4.2.1 that we have identified the significant variables (i.e., *Gender* and *Brand* for both R_r and R_c, *TimeLimit* and *Seasonality* only for R_r, and p and *Holiday* only for R_c), we concentrate our following discussions on how these significant variables influence the reading and conversion rates.

We can find that, for all the scenarios, *Gender* is positively correlated with the reading rate but it negatively influences the conversion rate. Presuming that most read and purchase records for the women's (men's) garments are generated by the female (male) customers, we learn that, compared to men's garments, women's can help attract more attentions from the potential, female customers.

	Variables	Scenarios								
		(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
R_r	a_0	−0.00732 (0.0409)	0.0244 (0.0491)	0.00743 (0.0247)	0.0363 (0.0269)	0.00142 (0.0219)	−0.0233 (0.0185)	0.0750 (0.0696)	0.00544 (0.0592)	0.0494** (0.0158)
	α^2				−0.0701*** (0.0263)					
	β					$5.43e-05$ $(4.50e-05)$	0.000122** $(5.74e-05)$		−0.000449** (0.000168)	
	β^2						$-8.40e-08$ $(7.42e-08)$		$1.09e-06$** $(4.25e-07)$	
	Gender	0.0215 (0.0296)	0.0232 (0.0527)	0.0440 (0.0368)	0.0206 (0.0144)	0.0353** (0.0167)	0.0225* (0.0123)	0.0178 (0.0306)	0.0313 (0.0259)	0.0140 (0.0152)
	Brand	0.0569 (0.0346)	0.0104 (0.0251)	0.00757 (0.0279)	0.0293** (0.0116)	0.0151 (0.0144)	0.0371*** (0.0129)	−0.0401 (0.0637)	0.0551 (0.0497)	−0.0142 (0.0152)
	TimeLimit	−0.0168 (0.0146)	−0.0165 (0.0152)	−0.00899 (0.0177)	0.0169* (0.00895)	0.0220** (0.00844)	0.00355 (0.00757)	−0.0228 (0.0225)	0.0111 (0.0155)	−0.0163 (0.0124)
	Spring	−0.00102 (0.0219)	0.0279 (0.0194)	0.0299 (0.0188)	0.0221 (0.0140)	0.0247* (0.0127)	0.0427*** (0.0132)	0.0468* (0.0262)	0.0547*** (0.0197)	0.110*** (0.0236)
	Summer	0.00698 (0.0238)	0.0277 (0.0208)	0.00604 (0.0191)	0.0311** (0.0144)	0.0279** (0.0128)	0.0303** (0.0122)	0.0173 (0.0423)	0.0101 (0.0268)	
	Autumn	−0.0132 (0.0224)	0.00370 (0.0194)	0.0294 (0.0177)	0.0178 (0.0154)	0.0251* (0.0142)	0.0322*** (0.0114)	0.0251 (0.0262)	0.00426 (0.0194)	0.0451** (0.0170)
	Observations	31	70	32	103	142	86	29	50	14
	Adjusted-R^2	0.051	0.039	0.132	0.157	0.115	0.269	0.013	0.225	0.719
R_c	a_0	−0.00651 (0.0215)	0.0556*** (0.0136)	0.0562 (0.105)	0.0511*** (0.0114)	0.0157* (0.00879)	0.000649 (0.0281)	−0.00275 (0.0356)	0.000573 (0.0421)	0.00947* (0.00428)
	α	0.0226 (0.0651)	−0.182*** (0.0393)	−0.130 (0.290)	−0.144*** (0.0358)	−0.0306 (0.0253)	0.0177 (0.0766)	0.0858 (0.112)	0.0260 (0.116)	
	α^2	0.00376 (0.0579)	0.158*** (0.0304)	0.0985 (0.200)	0.127*** (0.0294)	0.0301 (0.0202)	−0.00891 (0.0532)	−0.0645 (0.0892)	−0.00367 (0.0833)	
	β				$4.10e-05$*** $(1.06e-05)$				$-1.71e-05$ $(1.02e-05)$	
	Gender	−0.00496 (0.00940)	−0.000115 (0.00427)	−0.00264 (0.00693)	−0.00435 (0.00292)	0.00195 (0.00194)	−0.000800 (0.00248)	$-0.0138**$ (0.00544)	−0.00710 (0.00438)	−0.00236 (0.00235)
	Brand	0.00903 (0.00932)	0.00387* (0.00199)	−0.00219 (0.00599)	0.00259 (0.00243)	0.00111 (0.00167)	0.000792 (0.00238)	0.00203 (0.0106)	0.00635 (0.00762)	0.00153 (0.00206)
	p	$-2.84e-05$ $(4.12e-05)$	$-1.49e-05$ $(1.05e-05)$	$-7.07e-06$ $(8.10e-06)$	$-2.55e-05$ $(2.17e-05)$	$-1.63e-05$* $(9.12e-06)$	$-3.32e-06$ $(3.63e-06)$	$-4.28e-06$ $(5.01e-05)$	$-1.79e-05$ $(2.71e-05)$	$-2.12e-06$ $(3.61e-06)$
	Holiday	0.00555 (0.00501)	−0.00137 (0.00196)	0.00943* (0.00494)	0.00348 (0.00210)	0.00216* (0.00114)	0.00395** (0.00183)	−0.00708 (0.00586)	−0.00177 (0.00286)	−0.00339 (0.00214)
	Observations	31	70	32	103	142	86	29	50	14
	Adjusted-R^2	-0.005	0.342	0.034	0.320	0.031	0.005	0.152	0.113	0.088

Table 7: The coefficients and standard errors for the reading rate function and the conversion rate function in the nine scenarios

However, the male customers who read the detailed promotion messages for the men's garments are more likely to buy than the female customers who read the promotions details for the women's garments. It thus follows that, in general, the female customers are more interested in browsing the shopping websites after they receive the promotion messages, possibly because of their shopping habits different from the male customers' habits. As in practice, the female customers may not have a clear purchase target prior to receiving a promotion message, or they may be accustomed to make comparisons before they make a purchase decision. However, as for the male customers, after they show their interests in a promotion program by clicking the hyperlink for more promotional information, they are more likely to purchase the promoted product vis-à-vis the female customers. This may be attributed to the fact that the male customers may have a specific before-purchase expectation with a high possibility. As a consequence, the promoted products that are close to their expectations can arouse their interests and induce them to browse the promotion details, thus rendering a higher conversion rate in comparison with the female customers.

Table 7 indicates that, except for scenarios (vii) and (ix) (which are concerned with the low- and high-priced products at the decline stage), variable $Brand$ is positively correlated with the reading rate. This variable also has a positive influence on the conversion rate for all the scenarios except for scenario (iii). The results mean that in the Chinese garment market, for most cases, the garments of foreign brands apparently outperform those of domestic brands in arousing potential customers' interests in the promotion details and also increasing their purchase intentions.

For the garments that are at the introduction stage of their life cycles, the reading rate is increasing in the time limit in any promotion program. However, the time limit has an opposite effect on the reading rate when the promoted garments are at the maturity stage of their life cycles. When a garment is first introduced into the market, it needs a sufficient time for potential customers to understand the garment's attributes (i.e., quality, popularity, and others) before they decide on whether to buy or not. For this case, a promotion with a short valid time may deliver a "negative" signal to potential customers, thereby reducing the customers' incentives to click the hyperlink and read the promotion details. On the other hand, a garment at its maturity stage has been sold to some customers in the market, and its attributes are commonly known to potential customers by the means of, e.g., past customers' reviews. For such a garment, a short-period promotion can attract the attentions from the potential customers with the knowledge of the garment's attributes. Thus, when they receive the promotion messages, they are likely to browse the promotion website for details.

All the seasons except for the winter are strongly, positively correlated with the reading rate in most scenarios. When we compare the coefficients for the spring, the summer, and the autumn in each scenario, we can find the hottest (most suitable) sale season for each scenario, as summarized in Table 8. One may note that, in general, the spring season appears to be a popular season for the retailer to launch her promotions, as in this season potential customers may possess a high incentive to buy garments. Specifically, for all the high-priced garments and all the garments at their decline stages, the spring is the best season for the retailer to launch the promotions for relevant garments and attract potential customers' attentions. Therefore, it could be the best choice for the retailer to promote the luxury, spring garments in the market. Moreover, the retailer should choose the spring season for the clearance of the inventory of the garments that are at their decline stages. Among all the seasons, the summer is also a popular season for promoting the low-priced garments at the introduction and maturity stages and the medium-priced garments at the maturity stage. The winter is a slack season for the garment promotions.

In accordance with our analysis, original price p is negatively correlated with

		Product Life Cycle		
		Introduction	**Maturity**	**Decline**
Price Level	**Low**	Summer	Summer	Spring
	Medium	Autumn	Summer	Spring
	High	Spring	Spring	—

Table 8: The hottest promotion season for each scenario

the conversion rate in all of the nine scenarios. This intuitive result means that a higher original price reduces the probability for potential customers to buy after browsing the promotion website. That is, the original price for a garment is one of the most important factors in attracting customers to buy the garment from the online retailer. The coefficients for variable $Holiday$ in the nine scenarios demonstrate that, except for scenario (ii), the garments at the introduction and maturity stages enjoy a higher conversion rate on holidays than on regular times, whereas the conversion rate for the garments at the decline stage is lower on holidays. This implies that although, as in practice, the retailer usually spends great effort on the promotion of the garments at the decline stage, on holidays these products cannot receive significant attentions from potential customers and any promotion for them may discourage customers from online purchases. We mainly ascribe the result to the fact that, customers generally are more willing to buy some new or mature garments on holidays.

Remark 3 We draw a number of managerial implications from our regression analysis for each scenario. First, in general, the female customers are more interested in reading the promotion messages sent by the retailer than the male customers. But, after reading the promotion messages, the male customers are more likely to purchase the promoted products vis-à-vis the female customers. Secondly, for most cases, the garments of foreign brands can receive more attentions and higher purchase incentives from potential customers than the garments of domestic brands. Thirdly, for the garments at the introduction stage, the retailer may need to set a sufficiently long valid time for her promotions, whereas for the garments at the maturity stage, the retailer may implement a short time limit for her promotions. Fourthly, the spring is the best season for the retailer to promote the high-priced garments and the garments at the decline stage. The winter is a slack season for any promotion. Fifthly, on holidays, the retailer should promote the garments at the introduction and maturity stages rather than the garments at the decline stage. ■

Based on our regression analysis for each scenarios, we can construct the functions for the reading and conversion rates in terms of the significant, independent variables. For example, for scenario (iv), we assign the values in Table 7 to the constant and the coefficients for the variables in (4). The profit functions with numerical parameter values generated by our regressions can be maximized to find the retailer's optimal discount depth α^* and optimal coupon value β^*.

5 Optimal Promotion Decisions and Sensitivity Analysis

In this section, for each scenario we maximize the retailer's profit in (2) to find her optimal decisions on the discount depth and the coupon value for a representative case. Then, we compare the optimal decisions and the resulting maximum profits for the nine scenarios to find the changes in the optimal decisions and also identify the "best" scenario with respect to the highest sales, the largest reading rate, the greatest conversion rate, or the highest profit. We also perform sensitivity analysis to examine the effect of some promotion-unrelated variables (e.g., the gender, the brand, etc.) and an important parameter (i.e., markup percentage λ) on the retailer's optimal decisions and her maximum profit.

5.1 The Retailer's Optimal Promotion Decisions for Each Scenario

From Section 4.2.2 we can find the functions of the reading and conversion rates in terms of the retailer's decisions and non-decision variables for each scenario. Now, we perform our maximization analysis for step 2 as mentioned in Section 3.3. We consider a representative case in which the numerical values of the non-decision variables are commonly chosen by the retailer in her practical operations. Following the descriptive statistics in Table 3, we assume the original price as 200, 350, and 500 yuan for the low-, medium-, and high-priced garments, respectively. In addition, to make the representative case more universal in terms of our data, we assign the most frequent values to other independent variables referring to Table 3, namely, $Gender = 1$ (female); $Brand = 1$ (foreign brand); $Holiday = 0$; $TimeLimit = 0$; $Spring, Summer, Autmum = 0$ (i.e., $Seasonality$ is the winter). Moreover, in our study, the average coupon redemption rate γ for the online garment retailer is 0.4, i.e., $\gamma = 0.4$; and the average markup percentage λ is 200%, i.e., $\lambda = 200\%$.

Substituting the above values into the retailer's profit function in (2), we can find the resulting objective function only in terms of decision variables α and β. To ensure that our optimal results are consistent with the real operations, we involve two constraints into our maximization problems. In the first constrain, the face value of the dollar-term, post-used coupon should not be larger than customers' payment amount in their purchases. In the second constraint, the sales volume for each promotion should be non-negative. According to our summary statistics in Table 3, we search for the optimal discount depth (i.e., α^*) in the range $[0.2, 0.9]$, and search for the optimal coupon value (i.e., β^*) in the range $[0, 500]$. Actually, to the best of our knowledge, if the discount depth is less than 0.2 in practice, then there would be no difference to customers between the promotion with such a discount and the regular sales with no discount.

After setting the parameter values, the two constraints, and the value ranges for decision variables in the representative case, we use the Maple mathematical software with the GlobalOptimization package to obtain the optimal discount depth and coupon value (i.e., α^* and β^*) that maximize the retailer's profit for each scenario. For the nine scenarios, we then calculate the resulting sales $s(\alpha^*, \beta^*)$, reading rates $R_r(\alpha^*, \beta^*)$, conversion rates $R_c(\alpha^*, \beta^*)$, and maximum profits $\pi(\alpha^*, \beta^*)$. Our computation results are presented in Table 9.

		Product Life Cycle		
		Introduction	**Maturity**	**Decline**
Price	**Low**	$(\alpha^* = 0.51, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$978;$ $s(\alpha^*, \beta^*) = 30;$ $R_r(\alpha^*, \beta^*) = 7.11\%;$ $R_c(\alpha^*, \beta^*) = 0.43\%.$	$(\alpha^* = 0.20, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$15,927;$ $s(\alpha^*, \beta^*) = 171;$ $R_r(\alpha^*, \beta^*) = 8.34\%;$ $R_c(\alpha^*, \beta^*) = 2.05\%.$	$(\alpha^* = 0.40, \beta^* = 73)$ $\pi(\alpha^*, \beta^*) = \$2,425;$ $s(\alpha^*, \beta^*) = 46;$ $R_r(\alpha^*, \beta^*) = 5.27\%;$ $R_c(\alpha^*, \beta^*) = 0.88\%.$
Level	**Medium**	$(\alpha^* = 0.20, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$22,793;$ $s(\alpha^*, \beta^*) = 140;$ $R_r(\alpha^*, \beta^*) = 5.80\%;$ $R_c(\alpha^*, \beta^*) = 2.41\%.$	$(\alpha^* = 0.20, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$6,889;$ $s(\alpha^*, \beta^*) = 42;$ $R_r(\alpha^*, \beta^*) = 5.18\%;$ $R_c(\alpha^*, \beta^*) = 0.81\%.$	$(\alpha^* = 0.46, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$3,150;$ $s(\alpha^*, \beta^*) = 43;$ $R_r(\alpha^*, \beta^*) = 9.18\%;$ $R_c(\alpha^*, \beta^*) = 0.47\%.$
	High	$(\alpha^* = 0.20, \beta^* = 0)$ $\pi(\alpha^*, \beta^*) = \$35,484;$ $s(\alpha^*, \beta^*) = 152;$ $R_r(\alpha^*, \beta^*) = 5.90\%;$ $R_c(\alpha^*, \beta^*) = 2.58\%.$	$(\alpha^* = 0.20, \beta^* = 111)$ $\pi(\alpha^*, \beta^*) = \$8,569;$ $s(\alpha^*, \beta^*) = 30;$ $R_r(\alpha^*, \beta^*) = 4.88\%;$ $R_c(\alpha^*, \beta^*) = 0.61\%.$	—

Table 9: The optimal discount depth and coupon value (i.e., α^* and β^*), and the resulting sales $s(\alpha^*, \beta^*)$, reading rates $R_r(\alpha^*, \beta^*)$, conversion rates $R_c(\alpha^*, \beta^*)$, and maximum profits $\pi(\alpha^*, \beta^*)$ for the nine scenarios

5.2 The Best Scenario for the Retailer: Comparison of the Optimal Results in All Scenarios

We use our results in Table 9 to compare the retailer's optimal promotion decisions (i.e., α^* and β^*), and the resulting sales, reading and conversion rates, and profits among the nine scenarios for the representative case defined in Section 5.1. For our comparison, we plot Figure 1 to show the retailer's optimal decisions for different scenarios. One may note from this figure that for more than half of the nine scenarios, the optimal discount depth reaches the lower bound of the search range for our optimization. This sheds light on the fact that the retailer mostly aims to increase her profit margin, while ensuring her minimum discount amount. Specifically, apart from influencing the reading and conversion rates, the discount strategy also affects the profit margin for each garment. That means a greater discount would lead to higher reading and conversion rates and thus higher sales. However, it also decreases the profit margin of the promoted garment. Hence, there is a trade-off between the increase in sales and the decrease in profit margin. The optimal discount determined as the lower bound of the search range, as indicated by Figure 1, implies that, for the representative case, the negative influence of the discount promotion on the profit margin dominates its positive effect on the sales for the retailer's retail operations of garments.

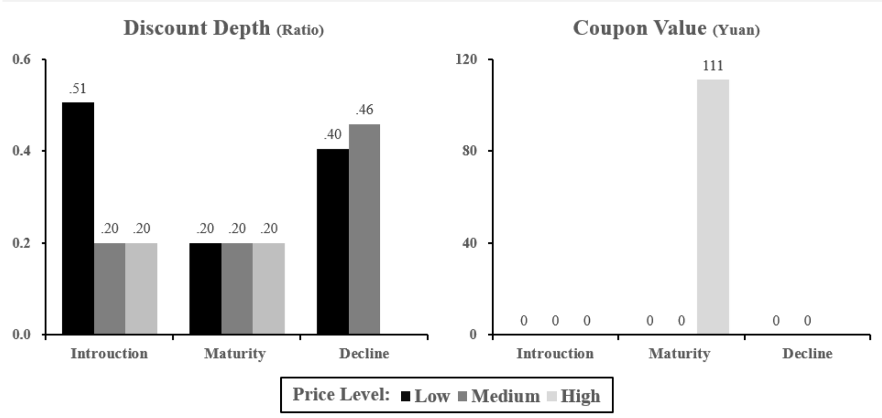

Figure 1: The retailer's optimal decisions α^* and β^* in the nine scenarios for the representative case

We learn from Figure 1 that, in the retailer's optimal promotion strategy, the price discount is a better promotion strategy for the low- and medium-priced garments at the introduction and decline stages, whereas the coupon is a better choice for the high-priced garments at the maturity stage. For all the garments at their introduction (decline) stages, the optimal discount depth for the low-priced garments is higher (lower) than that for the medium-priced garments. We also find that the price discount is not effective in improving the retailer's profit resulting from the sales of a garment at the high price level in its whole life.

However, the coupon plays an important role on raising the retailer's profit generated by selling the high-priced garments at their maturity stages. Nevertheless, neither the discount nor the coupon can help improve the retailer's profit made by promoting the high-priced garments at the introduction stage.

We plot Figure 2 to indicate the sales, the reading and conversion rates, the retailer's profit when the firm chooses her optimal decisions α^* and β^* in the nine scenarios for the representative case. The retailer can achieve the highest profit from promoting the high-priced garments at their introduction stages among all the nine scenarios. If we only consider the garments at the low price level, then these garments at the maturity stage are most profitable to the retailer, whereas those at the introduction and decline stages cannot bring any significant profit to the retailer. From the sales of the medium-priced garments, the retailer can enjoy the highest profit when the garments are at the introduction stage but obtain the lowest profit when the garments are at the decline stage. The retailer's profit resulting from the high-priced garments decrease dramatically from the introduction stage to the maturity stage.

Among all the garments, the retailer can enjoy the highest sales of the low-priced garments at the maturity stage. Moreover, for the medium- and high-priced garments, their sales at the introduction stage are significantly higher than those at the maturity and decline stages, at which these garments perform similarly as their sales are around 30 to 50 pieces. For most scenarios, the reading rate in terms of the retailer's optimal decisions is around 5%. The "best" scenario in which the retailer can achieve the highest reading rate 9.18% is scenario (viii) (i.e., medium-priced garments at the decline stage, as defined in Table 1). The second and third best scenarios are about the low-priced garments at the maturity and introduction stages, respectively. This means that, in general, the promotions for the low-priced garments can effectively arouse potential customers' interests. The figure for the conversion rate presents a similar pattern to the figure for the

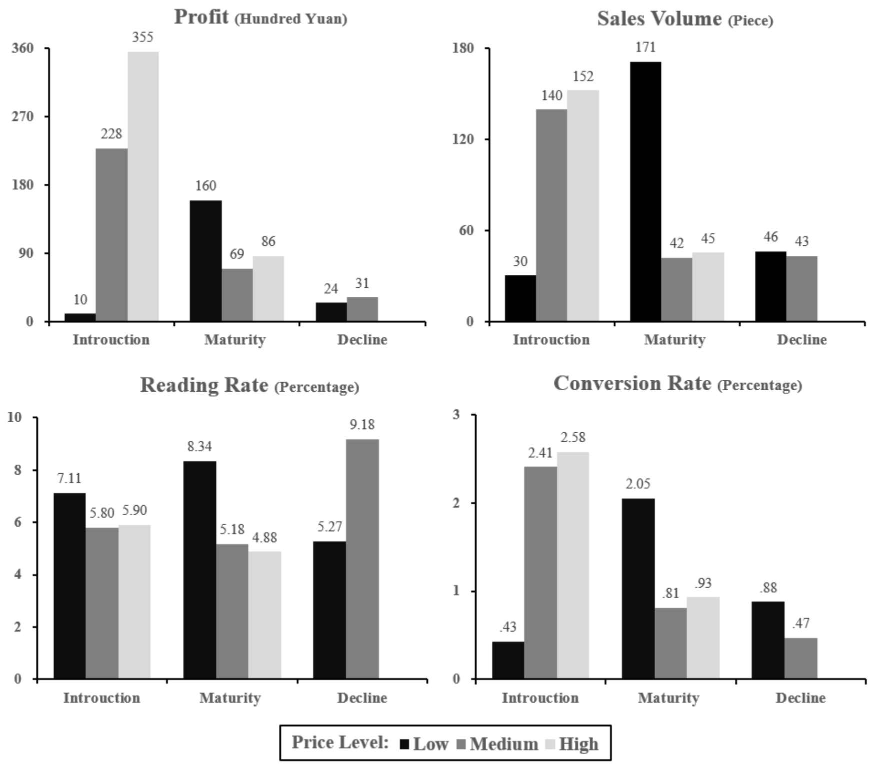

Figure 2: The sales, the reading and conversion rates, and the retailer's maximum profits when the retailer chooses his optimal decisions in the nine scenarios for the representative case

sales. We find that among the nine scenarios, the conversion rate is the highest in scenario (iii) in which the retailer promotes the high-priced garments at their introduction stages. The second and third highest conversion rates appear when the retailer promotes the medium-priced garments at the introduction stage and the medium-priced garments at the maturity stage, respectively. Moreover, we note from the figures for the reading and conversion rates that although potential customers are significantly interested in the promotions for the low-priced garments at the introduction stage, they seldom decide to buy these garments from the retailer.

Remark 4 After comparing the retailer's performances in terms of her optimal decisions in the nine scenarios, we find the best scenarios with respect to the sales, the reading and conversion rates, and the retailer's profits, as summarized in Table 10. One can note from Table 10 that the promotions of the high-priced garments at their introduction stages are the most important to the retailer in maximizing the conversion rate and her profit, whereas the low-priced garments at the maturity stage and the medium-priced garments at the decline stage are the best in maximizing the sales and the reading rate, respectively.

	Measurement			
	The Sales	**The Reading Rate**	**The Conversion Rate**	**The Profit**
The Best Scenario	Scenario (iv) (low-priced, maturity)	Scenario (viii) (medium-priced, decline)	Scenario (iii) (high-priced, introduction)	Scenario (iii) (high-priced, introduction)

Table 10: The best scenarios with respect to the sales, the reading and conversion rates, and the retailer's profits. The scenario numbers are defined as in Table 1. Each best scenario is denoted by the price level and the product life cycle of the corresponding garments, i.e., (low-/medium-/high-priced, intrdocution/maturity/decline)

We also learn from our comparison that the retailer considers the optimal discount depth to maximize her profit for most scenarios, but she only adopts the optimal coupon value for her profit maximization when she promotes the high-priced garments at the decline stage. In addition, the retailer can achieve a significantly high profit from promoting the medium- and high-priced garments at the introduction stage among all the scenarios. The sales of the medium- and high-priced garments are significantly high at the introduction stage, whereas those of the low-priced garments are significantly high at the maturity stage. In general, the changing patterns of the conversion rates in the nine scenarios are similar to those of the sales, and the reading rates do not significantly change for different scenarios. Moreover, our results reveal that for the low-priced garments at the introduction stage, many potential customers are significantly interested in the promotions but very few of them decide to buy from the retailer. ■

5.3 Sensitivity Analysis with Managerial Implications

We perform sensitivity analysis to examine the influence of some independent variables (i.e., the gender, the brand, the holiday, and the time limit) and markup percentage λ on the retailer's optimal decisions and her performance in terms of the sales, the reading and conversion rates as well as the maximum profit.

5.3.1 The Sensitivity Analysis of Gender

We change the dummy variable *Gender* from 1 (female) to 0 (male), and compute the resulting optimal decisions and performance of the retailer. We present our results for the retailer's optimal decisions in Figure 3. Comparing Figures 1 and 3, we find that, for those scenarios in which the optimal discount depth is higher than the lower bound of its search range (i.e., $\alpha^* > 0.2$), the discount depth is reduced by around 0.1 when the value of variable *Gender* is changed from 1 to 0. For other scenarios in which $\alpha^* = 0.2$, the change in the value of this variable does not alter the optimal discount depth. It thus follows that the retailer should set a higher or the same discount depth for the male garments vis-à-vis the female garments. Similar to our results regarding the optimal coupon for the representative case shown in Figure 1, the coupon still only plays a significant role for a few scenarios. Nevertheless, the optimal coupon value is higher for the high-priced, male garments at the maturity stage than that for the high-priced, female garments at the same stage. Different from the representative case, the retailer should involve a coupon (with the face value of 52 yuan) in her optimal promotion strategy for the medium-priced garments at the maturity stage.

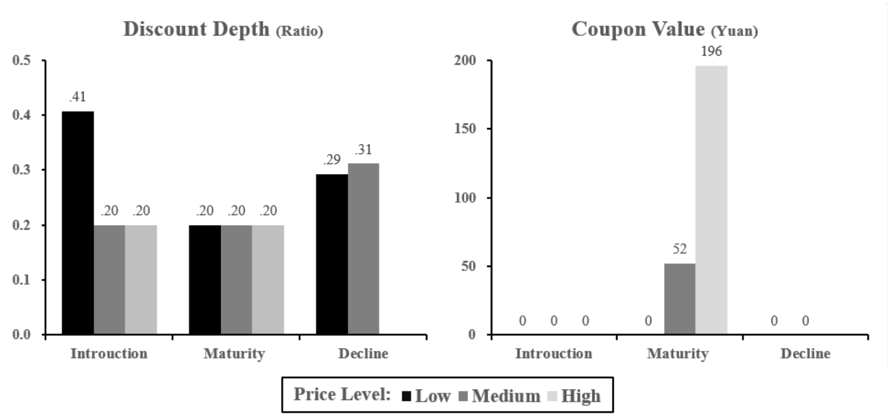

Figure 3: The retailer's optimal decisions when the value of variable *Gender* is changed from 1 to 0

For the retailer's performance when the value of variable *Gender* is changed to zero, we plot Figure 4 to indicate the results. Compared with the female garments as shown in Figure 2, the retailer's profits resulting from the male, medium- and high-priced garments at the introduction stage are significant smaller. Similarly, the profits from the male garments at the maturity stage are also lower than those from the female garments. However, the male garments at the decline stage bring a higher profit than the female garments at the same stage. This means that in general, the retailer could profit more from the female garments at the introduction and maturity stages, but achieve a higher profit from the male garments at the decline stage. The most profitable male garments should be the low-priced ones at the maturity stage, which is different from the representative case in which the most profitable female garments is the high-priced ones at the introduction stage. The changes in the sales are by and large similar to the fluctuations of the profits in the nine scenarios. We also learn from Figure 4 that the most popular male garments are the high-priced ones at the maturity stage, which is the same as our finding for the female garments.

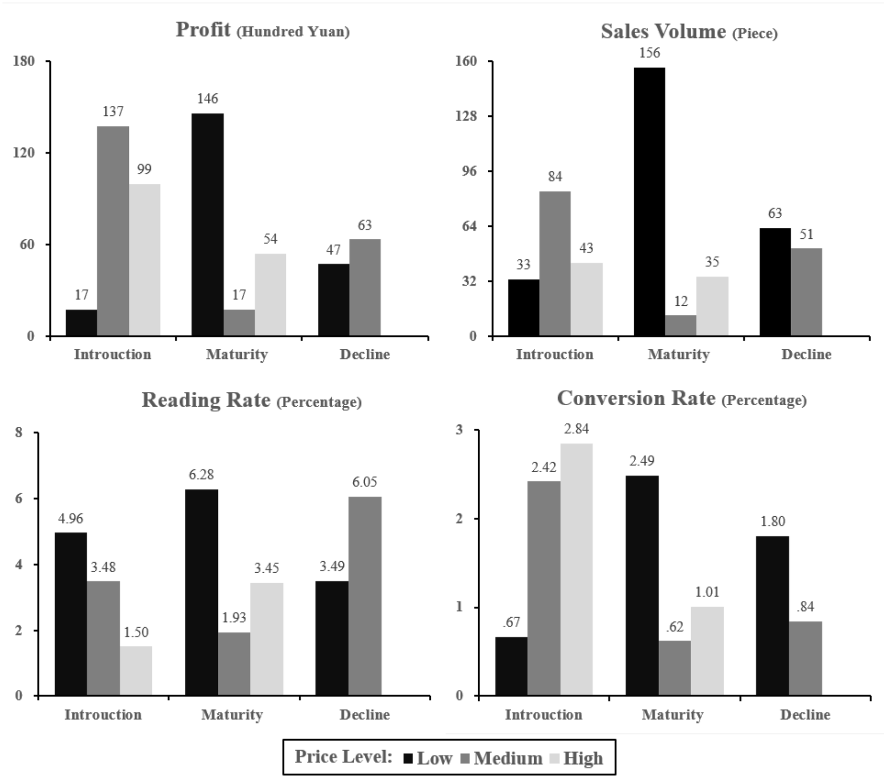

Figure 4: The sales, the reading and conversion rates, and the retailer's maximum profits when the value of variable *Gender* is changed from 1 to 0

Figure 4 also exposes that the reading rates for the male garments in all scenarios are smaller than those for the female garments, especially for the garments at the introduction stage. As a result, we can conclude that the female customers are more interested in clicking the hyperlink when they receive promotion messages than the male customers. However, the conversion rates for the male garments are higher than those for the female garments in all the scenarios except for scenario (v). That is, in general, the male customers who click the hyperlink are more likely to buy than the female customers. This is consistent with our relevant finding in Remark 3.

Remark 5 In general, the retailer's optimal discount depth for the male garments should be higher than or the same as that for the female garments, and the retailer does not involve any coupon strategy in her promotion plans for both the male and the female garments at the introduction and decline stages. Moreover, the retailer could achieve a higher profit from promoting the female garments at the introduction and maturity stages, but could have a higher profit from the male garments at the decline stage. The female customers are more interested in the promotion messages than the male customers, but are less likely to buy than the male customers. ■

5.3.2 The Sensitivity Analysis of Brand

We change the value of dummy variable *Brand* from 1 (foreign brand) to 0 (domestic brand), and compute the retailer's optimal decisions and the sales, the reading and conversion rates, as well as the retailer's profits for the nine scenarios. We learn from Figures 1 and 5 that the optimal discount depth and coupon value for the garments of domestic brands are greater than those for the garments of foreign brands, which may be attributed to the fact that the foreign brands are more attractive to potential customers than the domestic brands, as indicated by Remark 3. For the domestic-branded, low-priced garments at the introduction and decline stages, the discount strategy is an influential one; and, the optimal discount depths for the domestic brands are roughly identical to those for the foreign brands in each scenario. But, for the domestic-branded, high-priced garments at the maturity stage, the most profitable promotion strategy is to offer both a price discount and a coupon. More specifically, compared with the foreign-branded garments in this scenario, the optimal discount depth for the domestic brand increases from the lower bound of the search range to 0.29, and the coupon value for the domestic brand is doubled. For the garments at the decline stage, the discount depth for the medium-priced garments is reduced from

0.46 (for the foreign brands) to its lower bound 0.2 (for the domestic brands), while the coupon is involved into the retailer's optimal promotion strategy that maximizes her profit.

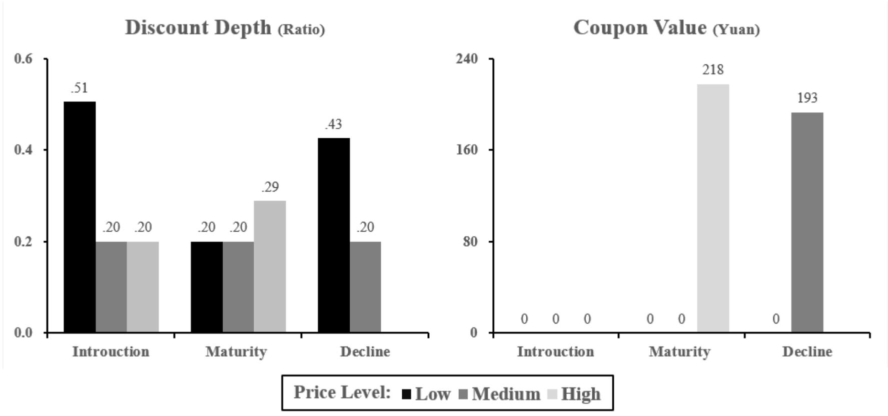

Figure 5: The retailer's optimal decisions when the value of variable *Brand* is changed from 1 to 0

We plot Figure 6 to show the retailer's performance in terms of her optimal decisions when the value of variable *Brand* is changed to zero. We learn from Figures 2 and 6 that the domestic brands are less profitable and less popular than the foreign brands in most scenarios. The most profitable garments of domestic brands are the same as those of foreign brands (i.e., the high-priced garments at the introduction stage), whereas the best sales garments of domestic brands are the high-priced ones at the introduction stage, different from those of foreign brands (i.e., the low-priced garments at the maturity stage). For the garments at the introduction stage, although both the profits and the sales for the domestic brands are smaller than those for the foreign brands, they are higher than those for other life cycles. For the garments at the maturity stage, even when the retailer implements a large discount depth and a great coupon value for the domestic brands, both the profits and the sales for these brands are still apparently smaller than those for the foreign brands. Moreover, it is interesting to observe that the medium-priced, domestic-branded garments at the decline stage is less profitable but more popular than the foreign brands in this scenario.

The low-priced, domestic garments at the decline stage are the only scenario in which the retailer achieves a higher profit and also higher sales than the foreign brands.

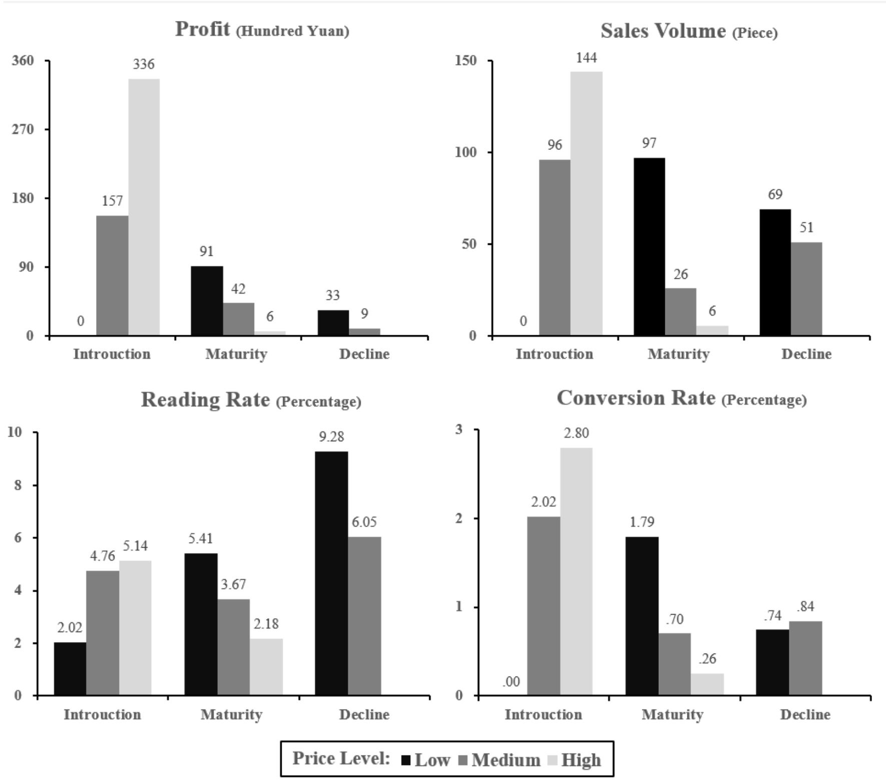

Figure 6: The sales, the reading and conversion rates, and the retailer's maximum profits when the value of variable $Brand$ is changed from 1 to 0

We note from Figure 6 that the garments of domestic brands receive a lower reading rate and also a lower conversion rate than the foreign brands in most situations. In all the scenarios except for scenario (i) (i.e., the low-priced garments at the introduction stage), the reading rates for the domestic garments are smaller than those for the foreign brands. The conversion rates for domestic brands are higher than those for foreign brands in scenarios (iii) (i.e., the high-priced at the introduction stage) and (viii) (the medium-priced at the decline stage). We also find that the conversion rate in scenario (i) is zero, which leads the sales and the retailer's profit to be 0.

Remark 6 The optimal discount depth and coupon value for the domestic-branded garments are greater than those for the foreign-branded garments. That is, the retailer has to spend greater effort to promote domestic garments than foreign ones. The retailer cannot enjoy a higher profit and achieve higher sales for domestic brands than the foreign brands in all the scenarios except for the promotions of the low-priced garments at the decline stage, for which the retailer can sell more domestic brands and also profit more from the brands. Moreover, the reading and conversion rates for the domestic garments are lower than those for the foreign brands in most scenarios. ■

5.3.3 The Sensitivity Analysis of Holiday

We change the value of dummy variable *Holiday* from 0 (the promotions on holidays) to 1 (the promotions on regular days). As Figures 1 and 7 indicate, the optimal discount depths and coupon values for the nine scenarios are similar for the promotions on holidays and those for regular days. For the low-priced garments at the introduction stage, the discount depth is reduced by 0.11 when the retailer change the promotion times from holidays to regular days. However, the discount depth for the promotions on regular days is higher for the garments at the decline stage.

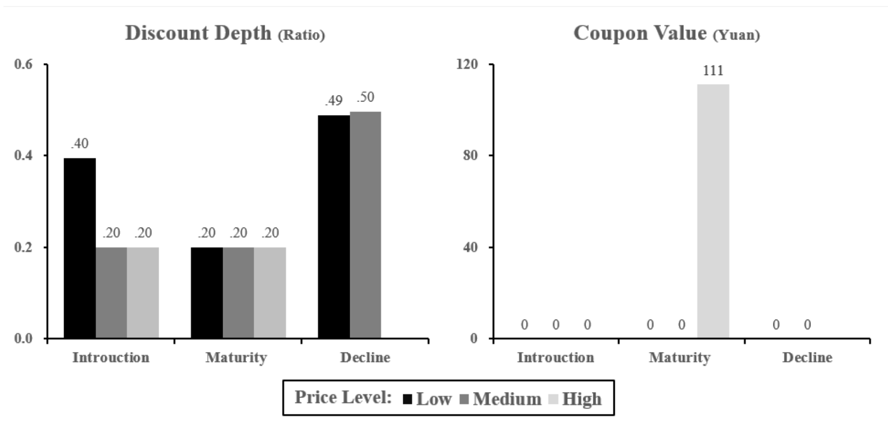

Figure 7: The retailer's optimal decisions when the value of variable *Holiday* is changed from 0 to 1

The retailer's performance in terms of her optimal decisions is shown in Figure

8. By comparing Figures 8 and 2, we can find that most results for the promotions on holidays are similar to those for the promotions on regular days. However, refer to Table 4, we can find that $Holiday$ is not a significant independent variable in the reading rate function but it exists in the conversion rate function. This means that whether a promotion should be conducted on a holiday or not does not alter potential customers' interests in the retailer's promotion messages, but it influences the purchase intentions of the potential customers who browse the website for more information about the promoted garments.

We interpret the retailer's profits for the nine scenarios as shown in Figure 8. At the introduction stage, the profits generated by selling both the low-priced and the high-priced garments are significantly higher on holidays, whereas those from the medium-priced garments are slightly smaller on holidays. For the garments at the maturity stage, the retailer's profits increase by around 2,000 yuan at three price levels when the retailer promote them on holidays. At the decline stage, the retailer's profits on holidays are apparently smaller than those on regular days.

Remark 7 The promotion time does not influence potential customers' attentions to the retailer's promotion messages, but the customers who browse the promotion information buy the garments with a higher probability on holidays. Compared to the promotions on regular days, potential customers show less intentions to purchase the garments at the decline stage on holidays. As a result, the retailer needs to offer a greater discount depth and coupon value to stimulate the conversion rates for the promoted garments. But, the sales of the garments at the maturity stage are better on holidays. For both holidays and regular days, the most profitable and highest conversion rate garments are the high-priced garments at the introduction stage. ■

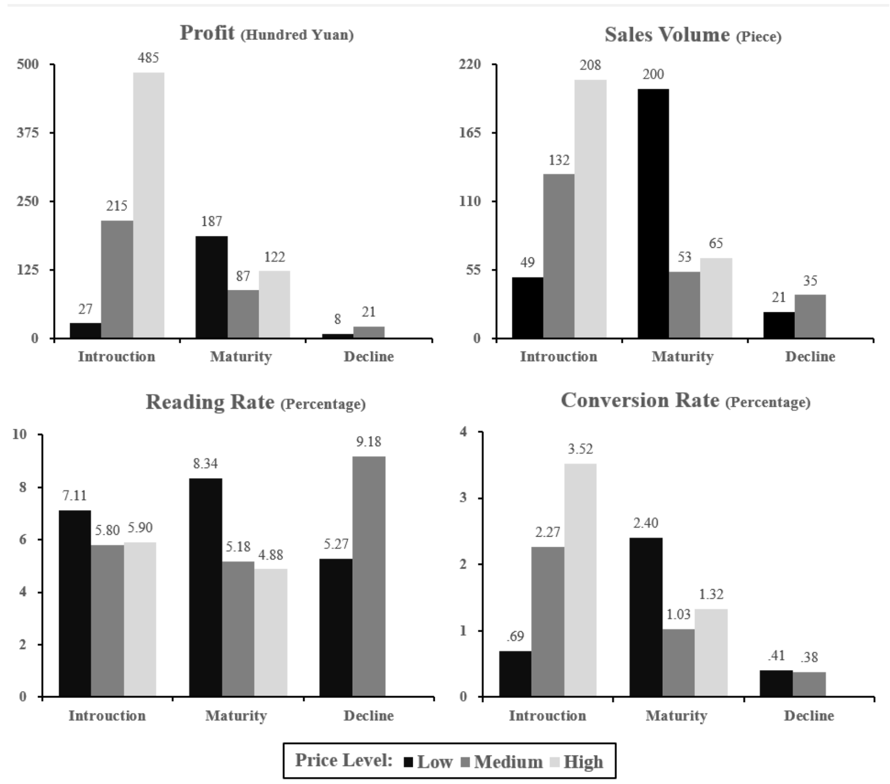

Figure 8: The sales, the reading and conversion rates, and the retailer's maximum profits when the value of variable $Holiday$ is changed from 0 to 1

5.3.4 The Sensitivity Analysis of Time Limit

We change the value of dummy variable $TimeLimit$ from 0 (with no time limit) to 1 (with a time limit). The optimal decisions for the nine scenarios are presented in Figure 9. The comparison between Figures 1 and 9 exposes that whether or not to impose a time limit for a promotion does not alter the optimal discount depth but reduces the optimal coupon value by a small number (i.e., 12 yuan) when the retailer promotes the high-priced garments at the maturity stage.

We plot Figure 10 to show the profit, sales, and the reading and conversion rates for the promotions with a time limit. One may learn from Table 4 that $TimeLimit$ is a significant independent variable in the reading rate function but does not influence the conversion rate. This means that whether to impose a time limit for a promotion or not can change potential customers' interests in the promoted garments, but it does not significantly affect the customers' pur-

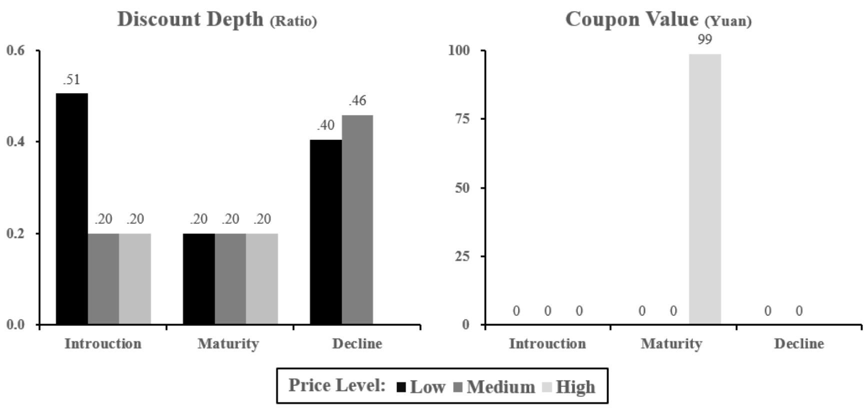

Figure 9: The retailer's optimal decisions when the value of variable $TimeLimit$ is changed from 0 to 1

chase intentions after they browse the promotion information. Different from the changes in the conversion rate, the sales, the profit, and the reading rate for the promotions with and without a time limit change in a similar manner. Accordingly, we only discuss the profit changes. For the garments at the introduction stage, the retailer's profit is reduced when a promotion involves a time limit. But, the profits from the promotions with a time limit is higher than those from the promotions with no time limit, when the garments are at the maturity stage. For the garments at the decline stage, the profits from the promotions with a time limit for the low-priced garments are lower, whereas those for the medium-priced garments are higher than those promotions with no time limit. The most profitable and the best sales garments are the same when the promotions have or do not have a time limit.

The time limit presents a "signal" of urgency and also a "signal" of the limited garment availability for a promotion, thereby acting as a stimulus for the promoted garments. If the promoted garment is a new entrant into the market, then the time restriction information in the promotion message may depress potential customers and thus reduce their interests in reading the promotion messages for more information about the promoted garments. However, for the garments at the maturity stage, potential customers have a knowledge of the attributes of

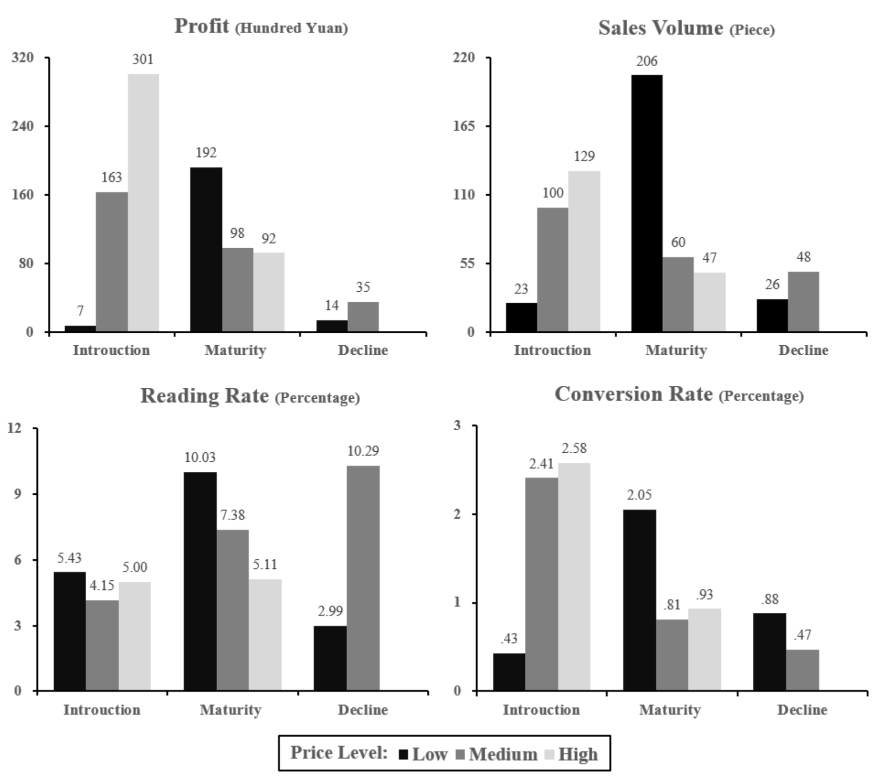

Figure 10: Corresponding Optimal Output Values of Changing TimeLimit from 0 to 1

such garments and thus, the involvement of a time limit in the promotions can generate a positive influence on the customers' interests. Nevertheless, our result shows that the existence of a time limit in a promotion does not significantly influence the customers' purchase decisions on promoted garments.

Remark 8 The optimal discount depth for the promotions with a time limit and that for the promotions with no time limit are the same, but the optimal coupon value for the promotions with a time limit is slightly smaller. Moreover, the involvement of a time limit in the promotions influences potential customers' interests but cannot affect their purchase intentions. Our results suggest that the retailer may not need to impose any time limit in the promotions for the garments at their introduction stages; but, it is necessary to involve a time limit into the promotions for the garments at the maturity stage. ■

5.3.5 The Sensitivity Analysis of Markup Percentage

As Section 5.1 indicates, for the representative case, an identical markup percentage value $\lambda = 2$ is used for the garments at the three price levels. In fact, this markup percentage value commonly applies to the medium-priced garments. It thus behooves us to examine how the optimal results change if the retailer differentiates the markup percentages for the high-, the medium-, and the low-priced garments, which are denoted by λ_h, λ_m, and λ_l. We compute the optimal decisions and the retailer's performance with the following two sets of the markup percentage values: $(\lambda_h, \lambda_m, \lambda_l) = (1.5, 2, 2.5)$ and $(\lambda_h, \lambda_m, \lambda_l) = (1, 2, 3)$, in which $\lambda_h < \lambda_m < \lambda_l$, because, as in practice, when the price level of a garment is higher, the markup percentage for the garment is usually greater. Since the results are similar to those for the representative case, we do not present any figure as in Sections 5.3.1, 5.3.2, 5.3.3, and 5.3.4. Nevertheless, we can still draw some interesting results as summarized in the following remark.

Remark 9 As the value of markup percentage λ increases, the retailer's maximum profit generated by promoting the low-priced garments decreases, whereas the profit resulting from the promotions of the high-priced garments increases. Moreover, for the low-priced garments, the optimal discount depth as well as the resulting conversion rate and sales are by and large decreasing in λ. However, for the high-priced garments, the optimal coupon value as well as the resulting reading rate and sales are increasing in λ.

The above findings suggest that, for a low-priced (high-priced) garment, the retailer may need to set a low (high) markup percentage and launch a promotion plan with a small discount depth (higher coupon value). ■

6 Summary and Concluding Remarks

In this thesis, we propose a three-stage approach to investigate the retailer's optimal promotion strategies for garments, which are classified into nine groups / scenarios based on their price levels and their life cycle stages. Apart from decision variables, other factors, such as brand, gender, holiday and etc., are also under consideration when we optimize the promotion stategy in different scenarios. For further analysis, we obtain a three-year promotion dataset from an online Chinese garment retail company who operates her online business at the QQ social media platform. Then we apply the three-stage approach on the dataset. In the first stage, we perform a two-step regression analysis. In step 1, we construct an aggregate regression model to identify the decision variables and the other independent variables that are significant correlated with the reading and conversion rates. From this step, we can find the most suitable promotion strategy for each scenario. In step 2, we divide our empirical data into nine categories each corresponding to a scenario. For each scenario, we construct the reading and conversion rate functions in terms of the significant variables identified in step 1, and conduct regression analysis to obtain the numerical values of the parameters for these variables. In the second stage, we build the retailer's profit function and maximize it to find the optimal decisions for her most suitable promotion strategy in each scenario. In the third stage, we compare the optimal results in the nine scenarios to recognize the best scenario with respect to the largest profit, the highest reading and conversion rates, and the greatest sales. We also perform sensitivity analysis to investigate the influence of some parameters on the retailer's optimal decisions and performance, which expose some managerial insights.

In this thesis, we summarize all the findings in a number of remarks. Next, we itemize the major managerial implications.

1. In general, the promotion strategy involving a discount depth is optimal for the garments at the introduction and decline stages, whereas the promotion strategy with a coupon value is optimal for the garments at the maturity stage.

2. For the garments at the introduction stage, neither a discount depth nor a coupon value can significantly influence potential customers' interests in the promoted garments. However, both the discount depth and the coupon value have a significant influence on the reading rate for the garments at the maturity stage. Thus, it may not be effective to launch a promotion for arousing potential customers' interests in the new garments. But, the promotions for the mature garments can significantly improve the reading rate.

3. The price discount plays a significant role in influencing the conversion rate for the promoted garments in most scenarios, whereas the coupon only has a significant influence on the low-priced garments at the maturity stage and the medium-priced garments at the decline stage.

4. The most profitable garments for the retailer are the high-priced garments at their introduction stages, which can also generate the highest conversion rate among all the scenarios. The retailer can achieve the highest sales by promoting the low-priced garments at the maturity stage, but she can realize the highest reading rate by promoting the medium-priced garments at the decline stage.

5. The spring season is the best one for the retailer to promote the high-priced garments and the garments at the decline stage, whereas the summer season is the best one to promote the low-priced garments at the introduction and maturity stages as well as the medium-priced garments at the maturity stage. In addition, the autumn is the best season only for the promotion of

the medium-priced garments at the introduction stage, and the winter is a slack season for any promotion.

6. The promotions of the female garments can result in a higher reading rate in the market than those of the male garments, whereas the conversion rate is higher when the retailer promotes the male garments. In general, the retailer's optimal discount depth for the male garments is higher than or the same as that for the female garments, and the retailer does not involve any coupon strategy in her promotion plans for both the male and the female garments at the introduction and decline stages. Moreover, the retailer could achieve a higher profit from promoting the female garments at the introduction and maturity stages, but could have a higher profit from the male garments at the decline stage.

7. The optimal discount depth and coupon value for the domestic-branded garments are greater than those for the foreign-branded garments. The retailer's profit and sales for domestic brands are lower than the foreign brands in all the scenarios except for the promotions of the low-priced garments at the decline stage. Moreover, the reading and conversion rates for the domestic garments are smaller than those for the foreign brands in most scenarios.

8. Most of the garments at the introduction and maturity stages have a higher conversion rate on holidays than on regular days, but the promotions for the garments at the decline stage generate a lower conversion rate on holidays. During the holidays, customers prefer to buy the garments at the maturity stage instead of those at the decline stage. For both holidays and regular days, the most profitable and highest-conversion rate garments are the high-priced garments at the introduction stage.

9. A time limit in the retailer's promotions influences potential customers'

interests but cannot affect their purchase intentions. We also find that the retailer may not need to impose any time limit in her promotions for the garments at the introduction stage, but she may need to consider a time limit in her promotions for the garments at the maturity stage.

In this thesis, there are several potential threats to the robustness of our findings, mainly related to the empirical dataset we used. The first threat is the sample size. During the subsample analysis, we divided the whole sample into nine portions, in which the subsample size may become too small to get the robust findings for some specific scenarios. The second is the data source. All our promotion data came from the same store, for which the findings may contain some endogenous bias. Another potential concern of robustness is the product category we chose. Due to the data restriction, we cannot guarantee that we have controlled all the factors which may have a significant influence on the promotion effectiveness regarding garment category. Therefore, using promotion data from other product categories may have different results. Fourthly, the retailer in our study serves the online customers in China only. The findings may not be robust to the dataset from the foreign market.

Accordingly, we suggest some future research directions. We can enlarge our sample size either by lengthening the data collection time or by collecting promotion data from different stores in the same product category within the same time period. Besides, we can also collect data samples from other product categories to test the robustness of our findings generated using data in the garment category. What's more, to understand the customers' behaviors in different countries better, this analysis can be extended by collecting and studying the empirical data from different countries.

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