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Empirical study of cashback affiliate strategy: Evidence from a cashback website

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EMPIRICAL STUDY OF CASHBACK AFFILIATE STRATEGY: EVIDENCE FROM A CASHBACK WEBSITE

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I hereby declare that this DBA dissertation is my original work and it has been written by me in its entirety.

I have duly acknowledged all the sources of information which have been used in this dissertation.

This DBA dissertation has also not been submitted for any degree in any university previously.

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Abstract

With the rapid development of internet technology, e-commerce has become increasingly prosperous with online shopping increasingly penetrating into the daily life of consumers. Online channel has become an indispensable channel for merchants to reach their customers. To improve sales performance and address competition from rivals, online merchants have developed various promotion methods. Cashback promotion has gradually become one of the popular promotion methods, and attracted attention from scholars. This paper aims to investigate the relationship between cashbacks and consumer behaviors using data on Taobao merchants on a large cashback website in China. Two studies with a large number of transaction data have been conducted. Using Discontinuity Regression Design (RDD), Study 1 identifies the causal effects of online merchants' reputation on the level of cashback and examines the moderating role of competition intensity between merchants' reputation and cashback level. Our results show that merchants with better reputation are less likely to provide high level of cashback. However, when the competition intensity is high, the impact of merchants' reputation on the cashback level becomes smaller than when the competition intensity is low. Study 2 investigates the impacts of cashback on business operations. Specifically, we examine how cashback affects product return and how the effects differ from those of coupon discount. We then discuss the moderating effect of business reputation. The results show that although coupon discount has a positive impact on the product return rate, the cashback level has a negative impact on the product return rate. The effect cashback on the product return rate is further influenced by the reputation of the seller， for merchants with high reputation, the inhibition effect of cashback level on return rate is stronger， but the impact of coupon discount on the return rate isn’t moderated by the reputation of the seller.

Keywords: Cashback Affiliate, Merchant Reputation, Merchant Cashbacks, Product Return, Coupon

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Chapter 1 Introduction

Over the past decade or so, online shopping has increasingly become an integral part of consumers' daily life in China. According to *the 50th Statistical Report on China's Internet Development* recently released by the China Internet Network Information Center (CNNIC), as of June 2022, China had 1.051 billion netizens, and its internet penetration had reached 74.4%. The number of online shoppers in China had reached 841 million, taking up 80.0% of all netizens. In 2021, China's online retail sales amounted to 13.1 trillion yuan. The rise of e-commerce has provided a new way for enterprises to acquire and serve their consumers. They can learn consumer needs, views, and requirements at any time, identify the changes in consumers' needs, and formulate proper promotion strategies to drive market demand. The Internet has enabled online marketing, an effective digital marketing strategy, to turn the network into a channel for communication, promotion and brand loyalty building. The increasing penetration of the Internet in society, as well as improved connection speed and cheaper services make it increasingly easy for all entrepreneurs and professionals (Pavel，2022). Sales promotions in e-commerce attract consumers to shop more easily than those in traditional channels. Thus, sales promotions are frequently launched on various festivals or holidays by online retailers and platforms (Hu & Tadikamalla, 2020). In addition to traditional promotion activities of "money off", "money back" and "consumption gift", online promotion has developed some new forms such as deposit lock-in, installment payment, group purchase, and cashback promotions. My thesis focuses on cashback strategies.

The feature that distinguishes cashback shopping is that consumers can view cashback offers and initiate purchases on the website of the cashback companies rather than directly with individual retailers. (Vana, Lambrecht & Bertini, 2017). As the earliest and most commonly-used cashback promotion channel, cashback website collects product information from major e-commerce companies, helping consumers choose desired products by comparison with others, and attracting consumers with cashbacks. After logging into cashback websites, consumers can earn certain amount of cashback, which they can withdraw or use for the next transaction, after they enter stores via the links of major online retailers recommended by the websites and finish the transaction process. Cashback websites are a specific type of affiliate marketing, which is "…a web-based marketing practice in which a business rewards one or more affiliates for each visitor or customer brought about by the affiliate's marketing efforts" (Schulman,2015).

In business practice, many cashback websites become popular worldwide. For example, Ebates, the largest cashback site in America, boasts more than 2,000 shopping websites and over 2.5 million customers. It has paid more than $800 million in cashback to over 10 million consumers since the inception in 1998. In 2013, Ebates members spent over $2.2 billion shopping through the site and its affiliates, and the company generated $167 million in net revenue. TopCashback was founded on 2005, the largest cashback store in the UK，officially hit the 15 million members mark in 2019，provides a platform for customers to interact with more than 4,000 stores, including some of the major stores in the country. 51fanli.com, one of the most popular cashback sites in China, has more than 15 million members, and pays over 10 million yuan in cashback every month. In the UK, in 2016 alone, Quidco paid more than $64 million in cashback to its 7 million registered users and facilitated nearly $1 billion of sales for 4,300 retailers, which took up 1% of the country's online sales. As of 2021, Rakuten's 12 million members in the U.S. had earned more than $1 billion in cash back at their favorite stores. In 2020, the revenue generated by online discount and cashback platforms corresponded to approximately 6.92% of total e-commerce sales in Brazil, amounted to six billion Brazilian Reals(Stephanie Chevalier,2021). According to the research of Statista Research Department (2022), 55 percent of respondents had used cashback feature during purchases in 2018. An industry study (PR Newswire 2011b) shows that 50% of retailers and 48% of manufacturers take cashback as part of the promotion mix for customer loyalty.

E-commerce has witnessed a steady growth with advances in digital technologies. However, one of the challenges faced by online retail is consumers' lack of trust of unknown sellers. As one of the most commonly used quality signals in online markets, seller reputation scores can influence consumer behavior (Heide, Johnson, & Vang, 2013). An interesting question is whether sellers' reputation scores also influence cashback. On the other hand, lack of the opportunity to "touch-and-feel" the products before purchase also results in a higher rate of product return (Mandal, Basu, & Saha, 2021). Scholars have done a lot of research on the factors that affect product returns. We are interested in understanding whether cashback also affect product returns. If so, do cashback and coupons have different impacts on the product return?

Cashback shopping is a growing trend in ecommerce. Consumers access cashback affiliate sites instead of the individual retailers' website. This paper aims to investigate the relationship between cashbacks and consumer behaviors using data on Taobao merchants on a large cashback affiliate site in China, making a meaningful discussion of cashback strategy. To achieve this goal, I did two studies in this paper. Using regression discontinuity design, the empirical analysis of Study 1 reveals that merchants with better reputation are less likely to provide high level of cashback to improve sales. When the competition intensity is low, merchants with higher reputation are less likely to provide high-level cashback than when the competition intensity is high. Using the random effects model, Study 2 shows that the impacts of cashback and coupon discount are different. Although coupon discount has a positive effect on the return rate, the cashback level has a negative effect on the return rate. The impact of cashback on the return rate is moderated by the reputation of the seller, but the impact of coupon discount on the return rate isn't moderated by the reputation of the seller.

This study yields several practical and theoretical implications in cashback affiliate strategy research.

First, the conclusion shows that merchants with a good reputation can appropriately lower the cashback level, while merchants that have not yet established a good reputation need to increase the cashback level appropriately when using cashback for promotion. When there are a large number of similar products sold on the platform, the cash back rate can be appropriately increased. When there are fewer similar products sold on the platform, the cashback rate can be appropriately reduced.

Second, Because the use of cashback will reduce the product return, but the use of coupons will increase the product return, when online merchants launch product promotions and pay attention to return rate at the same time, they need to balance the relationship between cashbacks and coupons. Second, Because the use of cashback will reduce the product return, but the use of coupons will increase the product return, when online merchants launch product promotions and pay attention to return rate at the same time, they need to balance the relationship between cashbacks and coupons. For sellers with good reputation, increasing the cashback level while reducing the coupon discount can more effectively reduce the return rate.

Overall, this study contributes significantly to the existing literature. Using discontinuity regression (RD) design, this study identifies the causal impacts of online merchants' reputation on the level of cashback. Understanding the relationship between online merchant reputation and cashback not only broadens the scope of online reputation research, but also enriches the online reputation theory. Additionally, this study investigates the influence of cashback on product return.

The content structure of this paper is arranged as follows: the first chapter introduces the cashback affiliate websites and significance. The second chapter is literature review, which briefly describes the current research on cashback affiliate strategy and identified the research gap. The third chapter introduces the research background and research methods. The fourth chapter is Study 1, which identifies the causal impacts of online merchants' reputation on the level of cashback by using regression discontinuity (RD) design, and studies the moderating effect of competition intensity between merchants' reputation and cashback level. The fifth chapter is Study 2, which investigates the impacts of cashbacks on product return, and compares the effects with those of coupon discount. The sixth chapter summarizes the theoretical and practical contributions of this study and discusses future research.

Chapter 2 Literature Review

In the following, section2.1 reviews the literature on cashback from three aspects related to this study. Section 2.2 and section 2.3 focus on reputation and product returns. Section 2.4 reviews the theoretical foundations of the research model. The last section identifies the research gap and positions the study in the existing literature.

2.1 Cashback

2.1.1 Business value of cashback affiliate websites

Scholars mainly have two views about the business value of cashback websites. On one hand, they believe that the innovative e-commerce model of cashback websites has certain market advantages. For example, Cooper (2009) believed that the advantage of the business model is to give customers direct guidance and create potential enthusiasts of low-price products who can play a better role in word-of-mouth marketing. Cashback entices consumers to read promotion information on cashback websites first and then decide what to buy, instead of deciding what to buy first and then looking for promotion information on cashback websites. Aul Nikkel (2008) pointed out that the emergence of cashback websites has made the affiliate network hidden behind consumers come to surface. The advantages lie in increasing transparency for online marketing, and helping merchants improve customer loyalty and better adapt to consumers' changing needs and preferences for brands. Aul Nikkel (2008) also believed that the rise of cashback websites will continuously squeeze the market share of price comparison websites and search marketing websites.

On the other hand, some scholars believe that the current cashback website model has some defects. James and Russell (2009) believed that there are two main problems with cashback websites. First, fierce competition forces merchants to lower price and puts competitive pressure on merchants selling similar products, thus affecting the operation value chain. Second, the business model requires tracking customer browsing records. Because confirmation of cashbacks mainly relies on the trace of users' clicks, the security and technical issues involved should not be underestimated.

2.1.2 Cashback affiliate strategy in supply chain management

Research on cashback strategy in supply chain management can be divided into manufacturer cashbacks and retailer cashbacks. For example, Wong et al. (2009) built a model with one supplier and multiple retailers and proved that cashback contract is conducive to supply chain coordination. Chiu et al. (2011) further studied supply chain coordination for risk-loving retailers under target sales cashbacks. They found that suppliers can coordinate the entire supply chain through flexible target sales cashback contracts. Wang et al. (2011) showed that manufacturer-to-retailer cashbacks can increase profits for both sides. Xing et al. (2012) studied the problems of price matching and selective cashback contracts in a supply chain consisting of one manufacturer and two retailers. Zhang et al. (2016) found that manufacturers' cashback promotions for consumers can effectively avoid the adverse effects of the grey market.

Gerstner et al. (1986) showed that cashback promotions help merchants achieve price discrimination, which is used to distinguish consumers with low reservation prices from those with high reservation prices in the market. Chen et al. (2005) analyzed the difference between cashback promotions and coupon promotions: consumers can redeem cashback bonus only after buying a product, while they can redeem coupons when buying a product. Lu et al. (2007) compared cashbacks with coupons and discounts, and pointed out that when selling the same product, cashbacks can better reflect price discrimination than coupons. Aydin and Porteus (2008) extended the model of Chen et al. (2005) by considering manufacturers providing cashbacks for both retailers and consumers at the same time. They found that manufacturer-to-consumer cashbacks can increase retailers' profits but reduce the profits of the supply end. Cho et al. (2009) studied how a single manufacturer and a single retailer make cashback decisions respectively when there is an up-front cost for providing cashbacks. Gilpatric et al. (2009) pointed out that the reason why some consumers fail to redeem cashbacks is that they overestimate the cost of redeeming cashbacks in the future. Khouja et al. (2010) found that in the supply chain system with a single manufacturer and a single retailer, if consumers' valuation of the product cannot match cashbacks, cashback promotions are always beneficial to the manufacturer. Based on the results of Khouja et al., Arya et al. (2013) further studied the effects of cashbacks on decision-makers in the supply chain system, and found that the cashback strategy is beneficial to manufacturers, retailers and consumers. Liang et al. (2013) studied how manufacturers and retailers should price their products when manufacturers implement the cashback strategy for consumers in the competition between manufacturers' national brands and retailers' own brands. Yang et al. (2015) deeply analyzed the different impact mechanisms of cashback promotion and daily fair-price promotion on retailers' profits. Yi-Chun et al. (2017) found that cooperation of cashback websites with multiple websites will bring most benefits to merchants, and the competition rising from the cooperation can improve the overall market efficiency. Moreover, merchants that are disadvantaged in terms of brand valuation should target price-sensitive consumers by offering cash cashbacks in a strategical way.

2.1.3 Effects of cashbacks on consumer behavior

A number of studies have focused on the effects of cashback on consumers' buying decisions (Ballestar et al., 2018). Ballestar, Grau-Carles and Sainz (2016), and Ballestar, Sainz and Torrent-Sellens (2016) examined customers' commercial activities and roles in social network. They found that cashback strategies increase the likelihood of customers to join to a social network. They further found that combining traditional marketing strategies with word-of-mouth recommendation is critical to the success of cashback business model, because these recommendations can increase customer acquisition and enhance loyalty of existing customers.

Vana et al. (2018) studied consumers' buying behavior in cashback shopping, they found two results. First, cashback increases the likelihood that consumers will make additional purchases through cashback company websites. Second, cashback increases the purchase size. Specifically, an additional $1 in cashback increases the likelihood of future transactions by 0.02%. Existing literature has proved that cashback financial incentive entices customers to buy more products, as well as big-ticket items.

The above-mentioned research shows that consumers are highly engaged in cashback websites, and contribute to continued purchases from and revenue for marketers (Ballestar et al., 2016). Vana et al. (2018) examined the robustness of the above arguments and mentioned the necessity for extensive research in the field of cashback.

2.2 Reputation

2.2.1 The impact of online reputation on price

In the past ten years, extensive studies have focused on the impact of sellers' rating (positive reputation or negative reputation, or both) on commodity transaction price, transaction volume and selling probability. One conclusion is that seller reputation has a significantly positive effect on the transaction price, the probability of selling, or the volume of the transaction. For example, McDonald & Slawson (2002), took limited edition of Barbie and classic comic books as research objects, and found that the seller's reputation had a significantly positive effect on the price. Houser & Wooders (2006) examined the auction data of a certain type of computer chip and found that the influence of the seller's reputation on the auction price was statistically significant. Their results showed that if the number of favorable comments increased by 15, the final price would increase by 5% or even 12%. Using the auction data of 14,627 mobile phones, Diekmann et al. (2014) showed that the sales volume and selling price of sellers with high reputation were significantly higher than those with low reputation.

However, there is no consensus on the effect of reputation on prices. Highfill & O'brien (2007) showed that the number of favorable comments from sellers has no significant effect on auction price and auction quantity. Similarly, based on the data from eBay, Wan & Teo (2001) found that there was no significant impact between the score received by the seller and the auction price. Ariely & Simonson (2003) studied the auction data of tickets for the Rose Bowl football game between Wisconsin vs. Stanford on eBay and found that the seller's reputation had nothing to do with the final transaction price. Some researchers also found that the relationship between reputation and price was not significant (Ye et al., 2009). Chen & Xie (2017) investigated 5,779 Airbnb housing in Austin, Texas, the US., and found that the functional features of Airbnb housing were significantly correlated with their prices, while the impact of a home's reputation on Airbnb prices is weak.

2.2.2 The impact of online reputation on sales

Reputation, an important signal seller quality, has a significant effect on consumers' purchase decisions (Corbitt et al., 2003). Some studies have found that there is a direct and significant relationship between reputation and sales. For example, Andrews & Benzing (2007), based on the auction data on eBay and using the binary Logit model, found that the higher the sellers' reputation is, the more likely the product will be sold. By analyzing data on online auction, Livingston (2005) found that sellers with high reputation would get more profits than those with low reputation, and high reputation would influence the auction behavior of buyers and more likely to bring actual sales. Eaton (2007) made use of the auction data of electronic guitar on eBay and also found that high reputation can improve the likelihood of sales. They found that negative comments from sellers of both auction data and price data reduced the likelihood of a sale. Rabby & Shahriar (2016) conducted an empirical study based on the analysis of the data from eBay sellers, and concluded that the auction results of commodities were not only significantly affected by the favorable and negative rates of sellers, but also sensitive to the medium rate. For sellers with a higher percentage of positive ratings, an increase in neutral ratings reduces sales. For sellers with a higher percentage of negative ratings, an increase in neutral ratings increases sales and revenue. Zhang & Zhang (2011) found that when the reputation level was lower than a certain threshold, the sales volume would be negatively affected by the reputation. When the reputation was above a certain threshold, a high reputation would increase sales. Sun (2012) found that users' ratings of products had a significant relationship with product sales.

The research literature on the relationship between reputation and price has been rich, and the logical relationship between the two has been basically clarified in theoretical research. However, in the field of empirical research, there is still some controversy about the empirical relationship between the two variables. The main reason lies in the possible endogeneity in the use of empirical methods. Therefore, this paper will use the RD to study the relationship between reputation and rebate, so as to fundamentally avoid endogeneity.

In addition, it can be seen from the review that there is no in-depth study on the relationship between reputation and cashback. I hope that my study can bridge the gap between the increasing use of cashback shopping and the corresponding lack of research.

2.3 Product Return

Product return can be categorized into defective product return and non-defective product return. Previous research on reasons for product return mainly focuses on defective product return caused by product quality. However, with the development of online retailing, product return includes not only defective product return, but also non-defective product return. Non-defective product return means consumers return products not because of product quality, but because of other factors.

2.3.1 Returns Management

The research on returns management mainly focuses on reverse logistics and measures for product return.

Reverse logistics is the set of activities including product return, reuse of products, material substitution, reprocessing, remanufacturing and waste disposal (Stock 1992). Hess & Gerstner, (1996) showed that separate nonrefundable charges can be used to profitably control for returns and the optimal charges increase with the value of the products ordered. Lee et al. (2014) proposed a model of reverse logistics to minimize transportation cost and argued that forward warehouse, reverse sorting and mixed facilities are the key to improving logistics efficiency.

Because the inability to touch or feel the physical product in an online environment, e-tailer's return policy plays an important role in consumer purchase behavior. As the popularity of e-commerce grows, return policy has become a strategic tool to enhance sales, customer loyalty, and drive incremental revenue (Pei, Paswan, & Yan, 2014).

Smith (2005) studied the risk attitude towards demand uncertainty and retailers' optimal return strategy on the basis of non-defective product return. The study concluded that enterprises should provide compensation for product return for retailers. Mostard (2006) considered non-defective product return in the supply chain when consumer demand and variance are fixed, and formulated corresponding policies to ensure the optimal number of product returns. Lembke & Rogers (2002) proposed that compensation for product return to consumers is linearly related to consumer demand for goods. They derived the equilibrium between product return and demand, and identified the optimal product return strategy for online shopping. McWilliams (2012) compared the relationship between competition and product return of high-quality and low-quality enterprises. They conclude that strict return policies go against the benefits of high-quality enterprises, so that high-quality enterprises should formulate lenient return policies. Janakiraman et al. (2016) studied factors affecting retailers' return policy and the effects of return policy on return rate from different perspectives. They found that the leniency of return policy is mainly reflected in five different dimensions, i.e., time leniency (e.g., 60 days vs. 30 days return policy), monetary leniency (e.g., offering 100 percent money back vs. 80 percent money back), effort leniency (e.g., no forms required vs. forms required), scope leniency (e.g., accepting returns on sale items vs. not accepting), and exchange leniency (e.g., cash back vs. store credit). Walsh & Möhring (2017) evaluated the influence of money-back guarantees, product reviews and return labels/advice on return rate. They found that money-back guarantees significantly increase return rate, product reviews lower return rate, and free return label has no effect on consumer returns.

2.3.2 Consumer Behavior of product return

Wood (2001) first studied the characteristics of consumer decision-making process in remote shopping compared with traditional shopping in physical stores from the perspective of consumer psychology. They used endowment effect to explain the influence of lenient return policies on consumer decision-making, and proved the quality signal effect of lenient return policies in a remote shopping environment through experiments. Bechwati & Siega (2005) analyzed the influence of the number and nature of cognitive responses on the odds of product return based on theories of choice, memory and attitude stability. Petersen & Kumar (2009) used empirical data to analyze the role of product return in transaction, identifying the factors in exchange process that could explain product return, and the influence of product return on consumer behavior . Anderson et al (2003) found that consumers have an expected value of a product before purchase, which is the estimated product value. If the expected value is lower than the price paid, customers may feel regret in advance; if the expected value is greater than the estimated value, they may buy the product. Under these assumptions, in e-commerce, as product return conditions gradually become lenient, consumers rely more on returns to reduce cognitive dissonance (Lee, 2015). The root cause of cognitive dissonance lies in uncertainties of online products, namely product quality uncertainty and product fit uncertainty (Hong & Pavlou, 2014).

Previous research on returns has focused on two aspects: model building and behavioral perspective. A small number of studies have dealt with the impact factors of returns, but no literature has yet examined the impact of cashback on returns. Coupon discounts and cashbacks are often used by sellers as promotional devices. Whether coupon discounts, which are also used as promotional devices, have different effects on returns. Whereas coupons offer deals up front, with the purchase of the product, rebates can be redeemed only after purchase. When consumers experience uncertain redemption costs, this difference translates to a difference in when uncertainty is resolved (Lu, & Moorthy, S. 2007). Does this difference lead to different effects on returns?

Loss aversion theory is often used in the study of returns. For example, Wood, S. L. (2001) used the endowment effect to illustrate the influence of lenient return policy on consumers' purchase decision-making process, and demonstrated the quality signaling function of lenient return policy in the remote shopping environment through experimental methods. Wang (2009) conducted a test on how return policy and endowment effect influence purchasing tendency and return rate. This experiment proved that endowment effect did affect the returning behavior of consumers. It showed that lenient return policies significantly increased initial purchasing tendency but did not increase return rate. They replicated the existence of endowment effect with Chinese subjects in a typical setting of buyer and seller comparison. The endowment effect can be derived from loss aversion, as incorporated in prospect theory (Kahneman and Tversky, 1979). Therefore, this paper also uses the loss aversion theory to construct the model.

2.4 Loss Aversion Theory

Study 2 investigates the impacts of cashbacks on product return and compared the effects with those of coupon discount. Lu, & Moorthy, S. (2007) have compared coupons and rebates in terms of how they work as price-discrimination devices. They concluded that the advantage of coupons over rebates becomes even more decisive when consumers are risk averse, and risk aversion of consumers reduces the attractiveness of rebates. In order to better explain this risk aversion, this study builds upon the loss aversion theory to construct the research model.

2.4.1 The endowment effect

Loss aversion was first proposed by Kahneman and Tversky (1979), which originates from the fact that most subjects believe that gambles with equal odds of winning and losing are unattractive. This phenomenon can be explained by loss aversion, which reflects people's asymmetric sensitivity to losses and gains. The loss aversion theory suggests that losses loom larger than gains compared to a reference point, and individuals feel twice the pain of loss than the equivalent pleasure of gain (Knetsch & Thaler, 1991).

Loss aversion is the characteristic of all decision makers (Feng, Keller & Zheng, 2011). Loss aversion can occur in both riskless and risky domains. In riskless domains, people tend to value the items they own more highly than they would if the items did not belong to them, a phenomenon known as endowment effect (Thaler, 1980). In the experiment of Kahneman et al. (1990), everyone in the seller group received a mug in advance, and chose the lowest price within a certain range at which they were willing to sell the mug. Another group of buyers was asked to indicate the maximum price they were willing to pay for the mug. A third group of choosers chose to receive a mug or receive the indicated amount in cash. The study found that for the same mug, the median values were $7.12 for sellers, $2.87 for buyers, and $3.12 for choosers who choose cash. Obviously, sellers placed a much higher value on the mug than buyers and choosers. This endowment effect is seen as loss aversion in riskless domains, i.e., the seller's pain (disutility) from losing the item is far greater than the buyer's happiness (utility) from getting the item. The endowment effect has been proved in both experimental (Kahneman et al. 1990; Tversky & Kahneman, 1991) and empirical studies based on real data (Hoyer et al., 2002).

2.4.2 The status quo bias

Status quo bias is also seen as an important manifestation of loss aversion in riskless domains (Novemsky & Kahneman, 2005; Tversky & Kahneman, 1991). It mainly refers to the fact that decision makers are more inclined to maintain the status quo rather than make changes (Samuelson & Zeckhauser, 1988).

In the study of Knetsch (1989), each student of one class received a chocolate bar, and each student of another class received a mug. Students could freely trade the gift they had for another one. Although the trading procedures were simple, about 90% of students refused to do so and continued to hold their gifts. This phenomenon bias can be explained as when an individual is faced with a choice, taking the status quo as a reference point, any change in the status quo is regarded as a loss. Compared to gains brought by the change, decision makers tend to be more sensitive to losses, so that they choose strategies to maintain the status quo (Samuelson & Zeckhauser, 1988).

Both endowment effect and status quo bias are specific manifestations of loss aversion in riskless domains. Despite the overlap between the two concepts, they differ in the specific decision-making scenarios and objects. Endowment effect is about a certain item. When someone owns the item, his valuation of the item increases due to the ownership effect. The status quo bias is about a certain state. Decision makers tend to maintain the status quo rather than make a change, which is manifested as avoiding making decisions (Anderson, 2003; Morewedge et al., 2009).

2.4.3 Loss aversion in risky domains

In risky domains, the most typical example is the research that found most subjects were unwilling to participate in the gamble of 50/50 chance to gain or lose 50 yuan. From a numerical point of view, the expected return of participating in the risky gamble was 0, which was not different from the no-loss and no-profit outcomes of not participating. However, because of loss aversion, the disutility of a loss was far greater than the utility of a gain, so the actual utility of the gamble was negative, lower than the zero utility of not participating (Kahneman & Tversky, 1979). Tversky & Kahneman (1992) also found that only when the potential gain of the gamble increased from 50 to 100 yuan did the subjects believe that the pain brought by potential losses can almost offset the pleasure brought by potential gains.

Loss Aversion has implications for marketing. Most of the experiments on endowment effect have examined the instant endowment effect that is experienced immediately after an object is obtained (Wang, 2009). I believe that loss aversion can explain the return behavior in this study.

2.5 Research Gaps

Extant research on cashback has produced relatively fruitful results. However, there are still some research gaps.

First, previous studies on reputation of online merchants mainly focus on the relationship between reputation and consumer's shopping behavior, . In studies on the relationship between merchant reputation, the price and the sales volume, most existing research only examined the correlation between the variables and failed to solve the endogenous problem among them. This paper intends to add some theoretical contributions in the following aspects: Firstly, this study obtained unique transaction-level data from Taobao merchants on the third-party cashback platform. Secondly, in terms of research methodology, we will use regression discontinuity design to prove the causal effect of online merchant reputation on price, sales volume and cashback intention. Thirdly, this study examines the relationship between online merchant reputation and cashback intention, which broadens the scope of online reputation research on and further enriches the reputation theory.

The literature in product return has focused on the reasons for product return, product return management and consumer behavior. But there is little research on the influence of promotion methods on return behavior. In terms of research methods, most previous research has relied on analytical modeling, but there is limited empirical analysis. Moreover, different from existing research that mainly focuses on enterprises, this study takes the perspective of consumers. We obtained real transaction data and employed empirical analysis method to study the influence of different promotion methods on return behavior. This will complement the stream of research on product return.

In sum, this dissertation conducted original research on cashback and consumer behavior, took Taobao merchants on a large Chinese cashback platform as research subjects, collected a large amount of original transaction data for empirical analysis, focused on the relationship between merchant reputation and cashback level under the background of cashback shopping, and compared the effects of coupons and cashbacks on product return rates. Findings from this research offer important insights into merchants' effective cashback strategy in today's e-commerce environment.

Chapter 3 Research Setting

This chapter provides information and context about the research setting. Section 3.1 presents an overview of Taobao Alliance and Taobaoke. Section 3.2introduces the business model of Cashback Affiliate Website. Section 3.3 describes the development and cashback model of Super Tao that provided the research data for this paper. Section 3.4 introduces Mechanism of Taobao Store Dynamic Scoring Ratings (DSR). Section 3.4 describes the return process of online retailing.

3.1 Taobao Alliance

Taobao Alliance is a subsidiary of Alibaba Group, which was established by the merger of Alimama and Taobao. Alimama is an Internet advertising trading platform owned by Alibaba. It integrates small and medium-sized network media resources (such as small and medium-sized websites, personal websites, WAP sites, etc.) to form an alliance. The alliance platform helps advertisers realize advertising and monitors the data of advertising. According to statistics, advertisers pay affiliates advertising fees based on the actual effect of online advertising.

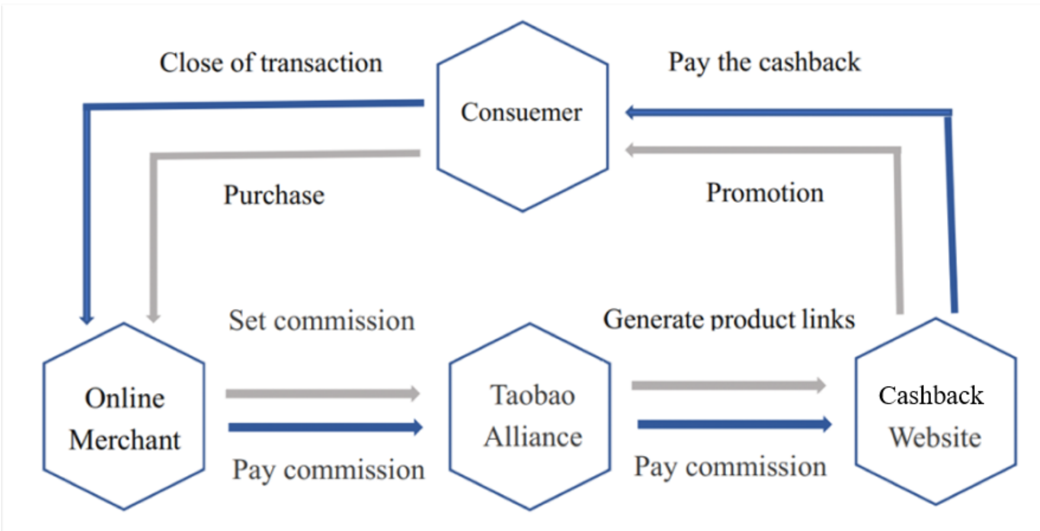

Figure 3-1 Transaction Process of Taobao Alliance

On April 8, 2010, Taobao Alliance was officially launched. Relying on Alibaba's powerful advertising resources and Taobao's massive commodity information, the C2C business model was adopted to obtain all kinds of Taobao customers' promotional commodity information through Taobao open platform and conduct in-depth mining. According to different filtering criteria relevant, Taobao commodity information is sent to the merchants, which reduces the time and costs for users to choose Taobao products, facilitates the completion of the transaction and makes statistical analysis on the display and click information of the clients. Taobao Alliance mainly serves Taobao. The sellers on Taobao and T-mall promote their products on Taobao Alliance by setting a certain cashback ratio. All kinds of websites, such as Taobao cashback net and Taobao Tmall internal coupon group, rely on Taobao Alliance.

Figure 3-2 Taobao Alliance interface

People who promote commodities and get commission in Taobao Alliance are called Taobaoke. Taobaoke only obtains the product promotion code from the Taobao customer promotion zone, and any buyer (including Taobaoke) enters a Taobao store through a link (personal website, blog or community post) published by Taobao Alliance, Taobaoke can get a commission paid by the seller. On the 21st of each month, Taobao Alliance will settle the last month income of Taobaoke, which is directly withdrawn in Taobao Alliance app or Taobao Alliance website. Afterwards, the commission will be deposited to the Alipay account.

Figure 3-3 Taobao Alliance commodity sharing interface

3.2 Cashback Affiliate Website

The affiliate cashback website is the upgraded version of Taobaoke. In order to improve the sales volume of products, most online retailers will promote sales through professional cashback websites, and pay a certain amount (or proportion) of commission to the cashback website according to the actual sales generated. In addition, the cashback affiliate website will return the part of the commission to consumers, namely cashback. It works as follows: after consumers enter the online mall to buy goods through the network interface provided by the cashback website, the cashback website will promise to return a certain profit. After consumers confirm the receipt of goods, the cashback website will remit the cashback (or equivalent virtual currency, discount card, coupon, etc.) to the consumer account, and consumers apply for withdrawal or use the cashback when they buy again.

The cashback model is a novel marketing solution, which combines promotion and price discrimination in the network environment. On one hand, it allows online businesses to expand their markets. Once the cashback websites are added, the merchants can publish a recommendation link, a hyperlink, to direct the traffic to the merchants' own online stores where the actual purchase transactions occur. Advanced network technology enables merchants to trace whether transactions are guided by recommended links. If a consumer purchases through these links, the cashback website acts as an intermediary to charge the merchant a fee. Then, it rewards consumers based on the announced cashback in advance to induce consumers to buy. This incentive induces some consumers to purchase in the original channel. On the other hand, the cashback model is also a pricing method to achieve market segmentation. For non-cashback consumers, the products can be listed at one price, while for cashback consumers, a lower price can be listed at the same time, so that businesses can implement three-tier price discrimination against consumers.

The current cashback websites adopt the CPS (Cost Per Sales) model (as shown in Figure 3-4), that is, they attract consumers through preferential cashbacks, and enable merchants to convert the advertising amount based on the actual number of products sold after they have concluded transactions with merchants. In the CPS mode, cashback websites directly cooperate with B2C Mall to provide API interfaces. The consumers enter the B2C merchant websites through the link given by the cashback websites. After the cashback websites cooperate with the advertising alliances to obtain the advertising codes, they also track the process of the consumers taking the goods, making payment and confirming the receipt according to the cookies. After the process is completed, the cashback websites will return part of the advertising fees drawn from the merchants to the consumers in a certain proportion, and at the same time, they will charge another part as the profit income. E-commerce platforms pay traditional advertising promotion fees to cashback websites and consumers in the form of commissions. Theoretically, this is a win-win model for three parties.

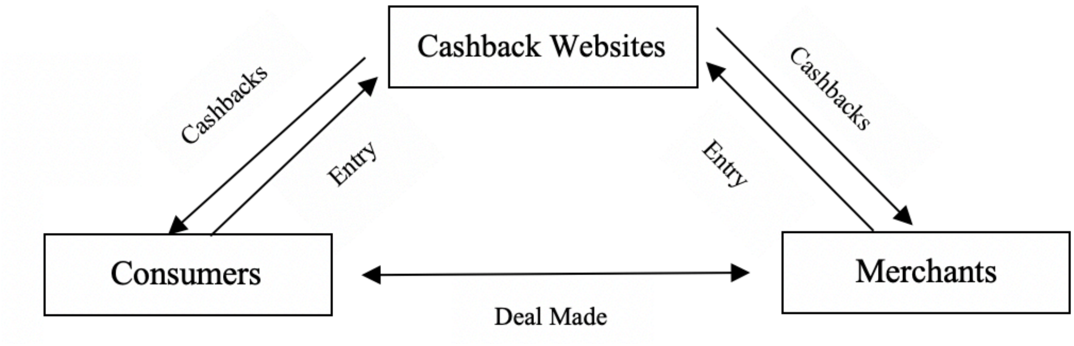

Figure 3-4 CPS Model

From the above process, we can see that the functions of the cashback websites are mainly reflected in the following two aspects: first, the cashback websites can make use of the influence of the website and the huge customer flow to lead customers to the merchants, and also reduce the publicity costs of the merchants; Secondly, "cashback" is the unique function of cashback websites, which enables consumers to get direct and practical discounts without bargaining with merchants, thus gaining the favor of the consumers. In addition, compared with other e-commerce models, online shopping cashback websites also have the advantages of simple and fast operation model and low cost. The main features are:

Neutrality. The cashback website provides cashbacks to customers and expands its influence by giving consumers preferential treatment. The cashback website does not involve the transaction details between consumers and merchants and is neutral in the transaction between commodity sellers and consumers.

Indirect. The amount returned to the consumers by the cashback websites cannot be obtained directly from the transaction through its link, but is subject to the transaction between consumers and merchants. For a certain amount of goods purchased by consumers, the merchants share the profits with cashback websites according to the sales price of the goods.

Discounts. After the consumer's transaction is completed, the merchant will pay a certain fee to the cashback websites which will share a proportion of the fee as rewards to consumers. The sales price of the commodity itself remains unchanged. If the traditional discount method is adopted, consumers may think that the goods are unsalable or have defects in quality, which will also damage the brand image. Sales through online cashback can protect the image of the goods and achieve the purpose of discount sales in essence. Some consumers who have not registered cashback websites directly enter the stores of the merchants and trade according to the price of the goods by direct purchase. In this case, the merchants will not generate profit sharing, and to some extent, it also helps the retailers to improve their profits.

3.3 Super Tao

Super Tao is an online shopping cashback APP, the samples used in this research are provided by the APP. The Super Tao app connects to four of China's most mainstream shopping websites, including Taobao, Tmall, JD.com and Pinduoduo. Users can get cash back just by shopping on these shopping platforms through the app.

Super Tao was established in 2016. By 2021, 8.716 million people have registered Super Tao, and the average daily active users has reached 36,100. In 2021, the total number of orders was as high as 297 million, and the total amount of order sales was 28.7million Yuan.

Because Super Tao is a shopping cashback APP, the goods linked by the Super Tao are all the goods promoted in major shopping platforms. Therefore, the data on the website is widely representative. The goods displayed on Super Taobao comes from two sources: 1) Comprehensive sorting from Taobao Alliance, Jingtiaoke, Duoduojinbao and third-party cashback affiliate websites (Dataoke.com, Haodangku.com, etc.); 2) The product selection team manually sorted and screened part of the products presented to users.When a user searches for a product, the available cashback is displayed on the product interface in the form of estimated annual revenue, so that the customer can make an informed purchase decision.

Figure 3-5 Product Interface of Super Tao

Different from the general cashback model, Super Tao employed a new form of “one spends, lasting cash back” model. That is, Super Tao cashback is based on the total amount of cost in each shopping platform to calculate the interest, and change the cashback from once per order to once a day. This means that super Tao shopping cashback is no longer based on the product or product cash back amount, as long as there is spending, there will be cashback. Even recharging phone bill can help earn cashback amount every day. The cashback can be withdrawn if it exceeds 1 yuan, and the account will be received two days after the application. Although the model of spending money is equivalent to saving money and earning interest is very novel, it is still essentially a cashback, because the upper limit of the annualized rate of return is determined based on the maximum cashback amount and dynamically adjusted according to the total amount of consumption.

Figure 3-6 Cashback Interface of Super Tao

3.4 Mechanism of Taobao Store Dynamic Scoring Ratings (DSR)

Taobao store dynamic scoring is a credit and service scoring system provided by Taobao for sellers. After purchasing goods, buyer can give seller an evaluation based on the condition of the goods and services. When other buyers buy goods, they refer to the buyer's goods and service attitude through dynamic scoring.

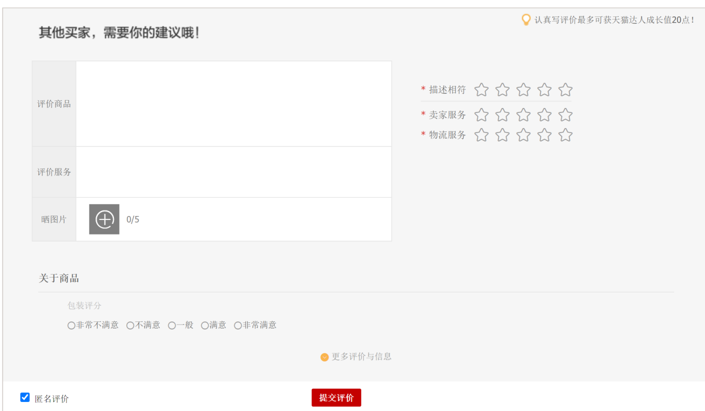

Figure 3-7 Figure Dynamic Rating Interface of Buyers

Taobao has three dynamic scores for sellers, which are "consistency in description of goods", "seller's service attitude" and "logistics service quality". The highest score for each item is 5 points, and the lowest score is 1 point. When the buyer purchases the goods, the seller is dynamically scored according to the specific situation. The final score of the seller is the average score of all the buyers and is displayed in the store information area. Because each transaction is different, the score given by the buyer will be different, so the dynamic score of the store will also change according to the transaction.

The DSR score of each seller is calculated as the ratio of the total score given by the buyers over the number of buyers who provided rating within 6 consecutive months. For example, assume a total of 20 buyers participate in the scoring, and each buyer only participates once, among which nineteen rate 5, and one rate 1. The dynamic average score is calculated as: 96 points (19 people * 5 points + 1 person * 1 point) divided by the total number of rating (20 times) = 4.8 points.

Figure 3-8 Dynamic Rating Interface of Stores

Taobao judges the comprehensive strength of a store by the dynamic score of the buyer to the seller, and accordingly allocates the support to the store, including the following aspects:

First, it affects search ranking. According to relevant regulations, the lower the index score, the lower the ranking.

Second, it affects the conversion rate. On the PC side, the store dynamic score is displayed on the store signboard, signaling the score reputation compared with peers. If the dynamic score of the store is floating green (floating green refers to the score of "description", "service" and "logistics" is lower than the normal score), or it is too poor compared with peers, it will directly have a negative impact on the conversion rate of the store.

Third, it affects participation in mall marketing events. The significance of the mall marketing events is to quickly improve the exposure rate of the store, so as to complete the accumulation of sales volume and customers. It is self-evident to improve the reputation and the level of the store. However, many mall marketing events have strict score restrictions on the dynamic scoring of the store, which directly affects whether they can register or pass the later audit.

3.5 Return Process of Online Retailing

Returns of Online retailing refers to the behavior that consumers return goods to merchants for various reasons after purchasing products. Returns involve four parties, including consumers, retailers, suppliers and logistics companies. When a return occurs, the consumer returns the goods to the retailer through reverse logistics, and the retailer returns the money to the consumer. This behavior is accompanied by the reverse transfer of the ownership of goods and currency.

The return service of most e-commerce enterprises is mainly managed by third-party service platforms such as e-commerce platforms. Taking Taobao as an example, when customers return a product, they complete the return and replacement according to the return process of Taobao platform: consumers contact the merchants' customer service to submit a return application or directly submit a return application on Taobao platform according to the page prompts. Generally, it is necessary to provide reasons for application and corresponding photographic evidence. After the merchant receives the return application submitted by the customer, there will be a 5-day processing period. If the merchant does not process the application after the expiration of the period, it is by default that the merchant agrees with the consumer's return application. The merchants shall make decisions on whether to approve the return of the consumers according to the communication results with the consumers or whether the application is true. If the merchant does not agree to return, the return application process is completed, and the consumer can appeal through other channels provided by the platform. If the merchant agrees to return the goods, the consumer returns the physical goods to the address designated by the merchant through logistics (third-party logistics or platform self-built logistics, etc.), and uploads the return logistics information on the platform to complete the return process. After the goods is received and confirmed, the merchant will return the payment amount of the order to the consumer. After the transaction between the two parties is completed, the return is completed.

In terms of the return logistics cost, the consumer and merchant decide who will pay the cost according to the ownership of responsibility. From the perspective of cost analysis, both consumers and merchants have cost in loss, including the logistics costs arising from the transportation and distribution of returned goods, the communication costs arising from the exchange of return communication information between the two parties, the financial costs of capital flow between the two parties, human and energy consumption costs, time costs, etc. It will do more harm than good to both sides. Therefore, it is undesirable for both parties to be involved in the return situation.

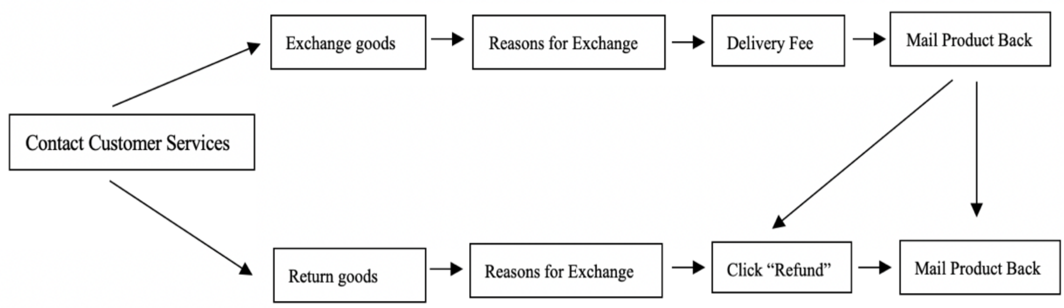

Figure 3-9 Return Process of Taobao

Chapter 4 Merchant Reputation and Cashback Level

4.1 Theories on Reputation and Competition

The booming development of e-commerce platforms has provided a more convenient and effective online transaction mode for buyers and sellers, and significantly lowered consumers' search costs. However, during online transactions, buyers face high risks because the virtuality, openness and anonymity of the Internet cause high information asymmetry in transactions on online shopping platforms. Sellers may behave dishonestly, such as exaggerating product quality, concealing product origin and delaying delivery, forcing buyers to take corresponding risks. This will make buyers less willing to shop online and pay the money, and may even result in low-quality sellers and products driving out high-quality ones. Worse still, this will cause high information asymmetry and market shrinkage, hindering the sound development of e-commerce platforms. In order to reduce the uncertainties in online buying and selling and build trust between buyers and sellers, online shopping platforms have introduced various measures, among which the reputation mechanism is widely adopted by almost all mainstream e-commerce platforms, such as Taobao, JD.com and Amazon. The online reputation mechanism collects reputation information of target individuals and disseminates the information in online communities, thus enhancing trust between buyers and sellers, avoiding adverse selection, effectively mitigating information asymmetry in online transactions, and promoting sustainable growth of online shopping markets. However, it is unknown how online reputation, an important signal of sellers' quality information, will affect the level of cashback offered by the sellers.

As one of the most common signals in online markets, reputation represents consumers' evaluation of sellers' past behavior and expectations for the future and is the type of signal that has received the most attention from scholars in research. It ensures that sellers smoothly convey product quality information and reduces the risk perceived by buyers. Reputation, as an important signal of sellers' quality, has a significant influence on consumers' purchase decisions (Corbitt et al., 2003). Since the quality of online sellers varies greatly, sellers that have more information can send signals to buyers, enabling them to distinguish high-quality sellers from low-quality ones (Bolton, Loebecke & Ockenfels, 2008), and attracting consumers' attention in the search and purchase process (Bockstedt & Goh, 2011). Van Der Heide et al. (2013) studied the influence of reputation system on consumer behavior based on signaling theory. Zhao & Sun (2013) found that on C2C e-commerce platform, store reputation has a positive effect on the number of product page views, and such positive effect grows with the increasing operation period. However, the main effect of store reputation on sales is not obvious. It has a positive interaction effect with the operation period, i.e., the longer the operation period, the greater the positive effect of store reputation on sales.

A good reputation can lead to numerous strategic benefits such as lowering firm costs, enabling firms to charge premium prices, attracting applicants, investors and customers, increasing profitability, and creating competitive barriers (Walker, 2010). Today, with the rapid development of digital economy, empirical studies on reputation have not examined the relationship between reputation and cashback. This study aims to fill this gap by showing that there is a significant effect of reputation on cashback.

The intensity of competition is also studied as a moderating variable in this paper. Competition intensity refers to the level of competition faced by the target enterprise in its industry (Sheng et al., 2013). Dufwenberg & Gneezy (2000) found that market price is affected by the number of competitors. Hou & Blodgett (2010) classified online auction markets into thick markets and thin markets and proved through empirical evidence that market structure has a remarkable influence on online auction price and product sales. Thick market refers to the market with a large number of sellers selling homogeneous products, while a thin market means the opposite. By comparing eBay US and Taobao China, Ye, Qiang et al. (2013) showed that in online market, it is the market structure, especially the number of sellers, that determines the relationship between seller reputation and sales performance. In thin market with fewer sellers, seller reputation is positively correlated with sales price, while in thick market with more sellers, seller reputation is positively correlated with sales volume (Ye, Xu, M., et al.,2013). We expect to see a cashback effect for high-reputation sellers due to the high degree of competition in a thick market.

4.2 Hypotheses

4.2.1 The Impact of Online Merchant Reputation on Cashback Level

Signaling theory is fundamentally concerned with reducing information asymmetry between two parties (Spence, 2002). For example, Spence's (1973) seminal work on labor markets demonstrated how a job applicant might engage in behaviors to reduce information asymmetry that hampers the selection ability of prospective employers.

Signaling theory also has a wide range of applications in management. Signalers in the management literature generally represent a person, product, or firm. Organizational behavior and human resource management (OB/HR) studies focus mainly on signals emanating from individuals (Connelly, etc.,2011). According to signaling theory, reputation as an important signal of seller service, has a significant influence on product pricing. As an important aspect of pricing, cashback is closely related to merchant reputation. Previous studies showed that merchant reputation can bring a price premium. In our context, it implies lower cashbacks, i.e., the higher the merchant reputation, the lower the cashback rate. Therefore, based on the above analysis, Hypothesis 1 is proposed as follows,

Hypothesis 1: Online merchant reputation has a significant and negative effect on cashback.

4.2.2 Moderating Effect of Competition Intensity

Cooper (2009) believed that the business model of cashback websites is attractive mainly because it provides direct shopping guidance for consumers by leveraging consumers' greed for cheap price and looking for potential enthusiasts of low price who can play a bigger role in word-of-mouth marketing. Therefore, many consumers decide what to buy based on the promotion information on cashback websites. The target group on these websites consists of price-sensitive customers who significantly value cashback experience. On cashback websites, consumers can see both product prices and cashback rates set by different merchants, which makes it quite easy for consumers to compare prices. Given the important influence of market competition intensity on product prices, it can be inferred that under fierce competition, merchants that face price-sensitive customers will gradually converge not only in product prices, but also in cashback rates. It means that the influence of reputation on the willingness to give cashback will decline accordingly. Based on signaling theory and the above analysis, Hypothesis 2 is proposed as follows,

Hypothesis 2: The influence of reputation on cashback level is smaller with high competition intensity than that with low competition intensity.

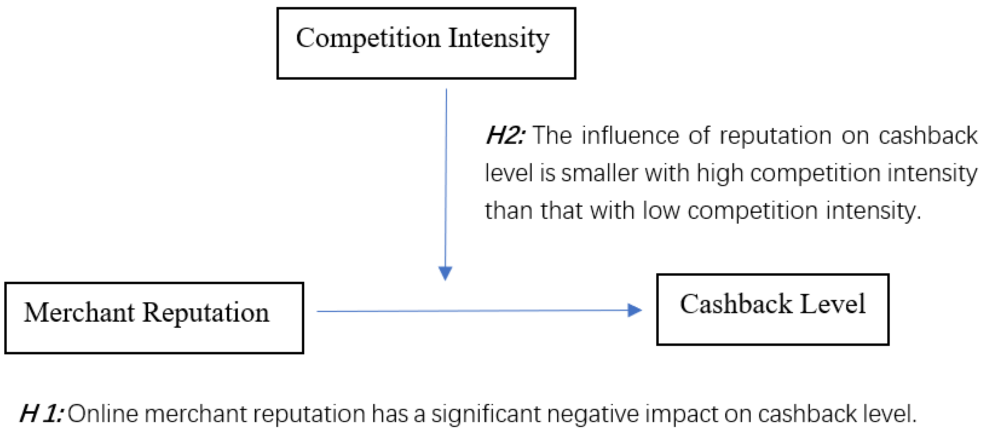

Figure 4-1 Theoretical Model for Study 1

4.3 Research Design

4.3.1 Sample Description

The samples used in this study come from a large cashback platform—Super Tao. I collected 1,894,027 transactions from the platform. Each transaction records three types of information, i.e., stores, products, and consumers. Since this paper mainly focuses on the analysis at the product level, the author consolidated data for each product and obtained 111,208product-level observations in total.

Dependent variable: In Study 1, the dependent variable is *CashbackRate*. It refers to the ratio of discount from the item price, expressed as a percentage in the database. Consumers observe and make purchase decisions in terms of expected annual returns on the product interface.

Independent variable: The independent variable is merchant reputation. In this study, the dynamic scores of merchants in the three aspects of Description, Service attitude, Logistics service are used to measure the reputation. They are denoted as AsDescribed, ServiceQuality and LogisticsQuality. These variables use percentages to measure whether a seller's reputation is above or below the industry average. Percentages are shown as positive when scores are above average and negative when scores are below average. The industry average is used a benchmark.

Alternatively, the following three variables are used to measure seller reputation.

$AsDescribedUP_i$: 0-1 variable, equal to 1 when the score of the merchant commodity i belongs is higher than the average of its peers, and 0 otherwise. With $AsDescribed_i$ measure, if $AsDescribed_i>0$, then $AsDescribedUP_i=1$. *AsDescribedUP* constitutes a cutoff on the description score.

$ServiceUP_i$: 0-1 variable, defined in a similar way as *AsDescribedUP*, measured by *ServiceQuality*, equal to 1 when the score of the merchant commodity i belongs is higher than the average of its peers, and 0 otherwise.

$LogisticsUP_i$: 0-1 variable, defined in a similar way as *AsDescribedUP*, measured by *LogisticsQuality*, equal to 1 when the score of the merchant commodity i belongs is higher than the average of its peers, and 0 otherwise.

Moderating variable: The moderating variable is *CompetitionIntensity*, which is used to measure competition intensity. It is measured by the number of similar products to the focal product that are sold simultaneously on the platform. Because of the large number of similar goods, I use *CompIntensIntensity*= number of similar goods /1000as measurement.

Control variables: *SellerID* is ID of Taobao seller. *ActualPrice* is Actual transaction price. *CashbackType* is the types of cashbacks, includes four types: General, Targeted, High cashback and RuyiTou. General type for all Taobaoke, commission ratio is generally 1~5%, after setting can't be deleted. Targeted type can choose Taobaoke, and the maximum commission can be set at 90%, after setting can't be deleted too. RuyiTou by Taobao alliance to find cooperation Taobaoke for promotion, sellers do not have to find and management Taobaoke. *DailySales* is one day's sales. In addition, since the sales in the data do not represent cumulative sales for 24 hours a day,*Accum_time* represents the recording time of this data, expressed as the number of seconds between that time and Zero Time divided by 3600. *CouponAvailable* refers to whether the seller has issued coupons, 0 is not issued, 1 is issued. *EarnestMoney* refers to whether the buyer has paid a deposit before making a purchase. After the buyer pays the deposit, at the final payment, it will be a certain amount cheaper than the normal price, and this amount is *ReductionMoney.*

Table 4-1 Description of Variables

变量名	定义	Mean	Std. Dev.	Min	Max
CashbackRate	Cashback ratio	23.96968	8.720394	2	90
AsDescribed	Percent on the description matches score	23.4556	25.59947	- 6.96	99.99
ServiceQuality	Percent on the Service quality score	23.01646	25.03914	-5.46	99.99
LogisticsQuality	Percent on the Logistics quality score	22.79426	25.32076	-4.5	99.99
CompetitionIntensity	Intensity of competition	304.8305	433.8021	1	1919
SellerID	ID of Taobao seller	8.36e+11	1.07e+12	5791	2.21e+12
ActualPrice	Actual transaction price	47.992	65.5579	55	999
CashbackType	0- General, 1- Targeted , 2- High cashback, 3- RuyiTou	2.971054	.2568375	0	3
DailySales	One day's sales	86.73773	1167.45	0	1100
Accum_time	The time from Zero Time to the present	.18.34236	.6.0015 72	.687 5	23.9991 7
CouponAvailable	0- no coupon issued, 1- coupon issued	.9941911	.075995	0	1
EarnestMoney	A deposit paid in advance	.0272013	.1.314456	0	100
ReductionMoney	A discount for paying a deposit.	.0432343	4.790781	0	1100

Note. number of observations is 111, 208.

By drawing the violin plots of the three explanatory variables (shown in Figure 4-1), we can clearly see that figures below the zero point are far less than those above the zero point, and are concentrated in a small interval near the 0-axis. This is mainly because consumers always choose merchants with high reputation and avoid those with low reputation, so that the order quantity of low-reputation merchants are significantly lower than that of high-reputation merchants.

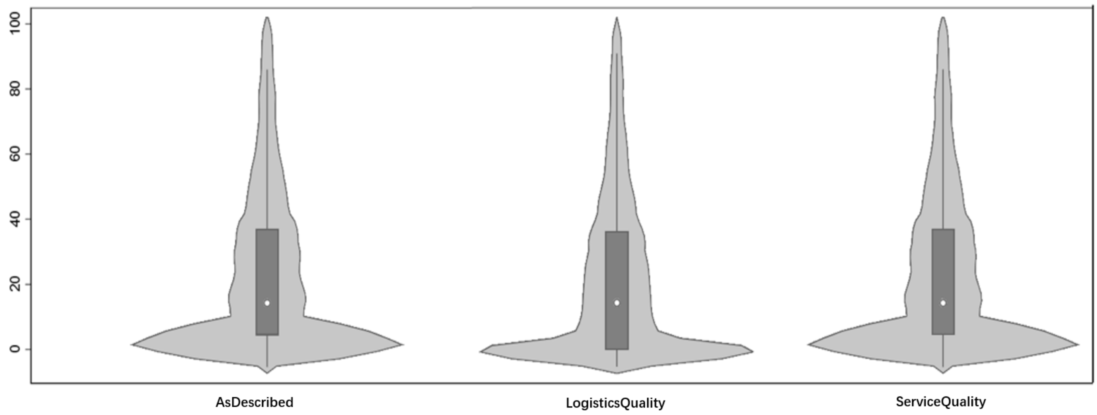

Figure 4-2 Violin Plot of the Reputation Variables

4.3.2 Regression Discontinuity Design

Regression discontinuity design was first proposed in 1958 by Donald Campbell, a psychologist at Northwestern University. Later, Thistlethwaite and Campbell (1960) published the first paper on regression discontinuity (RD). However, it was not until Hanhn (2001) proposed a rigorous theoretical proof for identification and estimation in regression discontinuity model that people gradually recognized the advantages of RDD. Lee, & Lemieuxa, T. (2010) show that the RDD is a much closer cousin of randomized experiments than other competing methods. Since then, RD gradually began to appear in the economics literature. Up to now, RD models can often be seen in fields such as labor and education economics, political economics, environmental economics and development economics.

RD is a quasi-random experiment, where the probability of treatment is a discontinuous function of one or more variables. When using an RDD, we need to define a running variable at first. When the variable is above the cutoff, it accepts treatment; when the variable is below the cutoff, it refuses treatment. In most cases, if an individual decides to accept treatment, it is impossible to know his situation when refusing treatment. RDD can help overcome this identification problem, with individuals below the cutoff regarded as control group. When the variables are continuous in particular, we can easily get clear picture on the causal relationship between the individuals that accept treatment and the outcome variables by examining the differences of outcome variables in samples around the cutoff.

RDD can be categorized into two types. The first type has a sharp cutoff point, which means all individuals on one side of the cutoff refuse treatment, all individuals on the other side accept treatment, and the probability of individuals accepting treatment changes from 0 on one side to 1 on the other side. The second type has a fuzzy cutoff point, which means near the cutoff, the probability of accepting treatment varies monotonically. Hahn et al. (2001) proposed that under certain conditions, the causal relationship with outcome variables can be analyzed by observing systematic changes of samples near the cutoff. Therefore, RD is an empirical method for studying the causal relationship between variables through restrictions on conditions after random experiment.

The basic idea of RD is to assume that before the experiment, there exists the following linear relationship between the dependent variable y_i and x_i: $y_i=\alpha_i+\beta x_i+\varepsilon_i$ ($i=1,\ldots,n$); when $D_i = 1$ ($x_i \geq c$) (c is the cutoff), the treatment effects are positive, and there is a cutoff point for upward jump in the linear relationship between y_i and x_i at $x = c$. Since there is no systematic difference among individuals in all aspects around $x = c$, the only reason for the jump in conditional expectation function $E(y_i|x)$ is be the treatment effect of D_i. Therefore, this jump can be seen as a causal effect of D_i on y_i at $x = c$.

In this paper, there is a clear cutoff in the dynamic reputation scoring system on Taobao, i.e., “industry average”. I propose that there is no systematic difference in merchant reputation within a few percentage points above or below the cutoff point. The only difference is whether the merchant’s reputation exceeds the industry average or not. Therefore, several percentage points above and below the "industry average" can be regarded as local randomization, and the RDD method can be used to identify the causal relationship between merchant reputation and cashback level. Let $D_i=\{0,1\}$ denote whether an individual merchant's reputation exceeds the industry average. The result we care about is y_i, i.e the cashback level. We try to figure out whether D_i (whether it exceeds the industry average or not) has causal effects on y_i (the cashback level). For individual merchants, there are two states for the cashback level.

$$y_i = \begin{cases} y_{1i} & \text{if } D_i=1 \\ y_{0i} & \text{if } D_i=0 \end{cases}$$

For individual merchant *i*, the industry average is denoted as *c*, and the reputation of merchant *i* is denoted as x_i. When $x_i \geq c$, $D_i=1$; when $x_i < c$, $D_i=0$. We apply a second-degree polynomial function to both sides of the cutoff and limit the value of *x* to $(c - h, c + h)$:

$$y_i=\alpha+\beta_1(x_1-c)+\delta D_i+\gamma_1(x_1-c)D_i+\beta_2(x_1-c)^2+\gamma_2(x_1-c)^2 D_i+\varepsilon_i \quad (c-h<x<c+h)$$

Specifically, y_i is CashbackRate, and the key explanatory variable x_i is merchant reputation level, which includes three variables: AsDescribed, ServiceQuality, and LogisticsQuality. The coefficient β measures the jump in cashback level at the cutoff. δ is an estimation of LATE. h is the optimal bandwidth. Intuitively, the smaller h is, the smaller the bias is, but the points close to $x = c$ are rare leading to a larger variance; on the contrary, the larger h is, the smaller the variance is, but the points relatively distant from $x = c$ leads to a larger bias. ε_i is a random disturbance term.

A few researchers have used RDD to study the causal relationship between online reputation and store sales. For example, Anderson & Magruder (2012) conducted a RDD with the cutoff in scores caused by Yelp's rating display mechanism to study causal effects of Yelp rating on the pre-visit rate of physical restaurants. Zhong (2014) employed a RDD relying on the discontinuity of Taobao's reputation rating system to study causal effects of reputation rating on the revenue of online stores. But there is no study identifying the causal relationship between online reputation and cashback level using RDD.

4.4 Empirical Analysis

4.4.1 RDD validity test

(1) Endogenous grouping/reference variable distribution continuity test

For RD analysis, sample data need to meet certain conditions. For example, except for treatment effects, other factors need to keep balanced and there is no selective sorting on both sides of the cutoff. Therefore, we need to check whether there is endogenous sorting before conducting RD. If individuals know grouping rules in advance and completely manipulate grouping variables through their own efforts, they can choose to enter treatment group or control group, resulting in endogenous grouping around the cutoff instead of random grouping. If there exists endogenous grouping, individuals will enter the experiment by themselves, leading to uneven distribution around the cutoff, so that the density function f(x) of the grouping variable x is discontinuous at $x = c$, and the left limit and right limit are not equal.

McCrary (2008) proposed a method for kernel density function, which divides running variable into different intervals and calculates the number of individuals in each interval. If individuals can manipulate the running variable (in our case, reputation), we will see obvious difference in the number of individuals around the cutoff. For example, if many individuals go to the right side of the cutoff through manipulation, the number of individuals in the interval on the right side may greatly exceed that on the left side. Through triangular kernel function tests, it can be seen that the confidence interval estimates of density functions around the cutoff of each variable overlap in a large part. Therefore, the grouping variable does not jump near the critical point, and density functions around the cutoff do not vary significantly. The testing result is that there is no endogenous grouping. The data in this study conform to the conditions of regression discontinuity analysis.

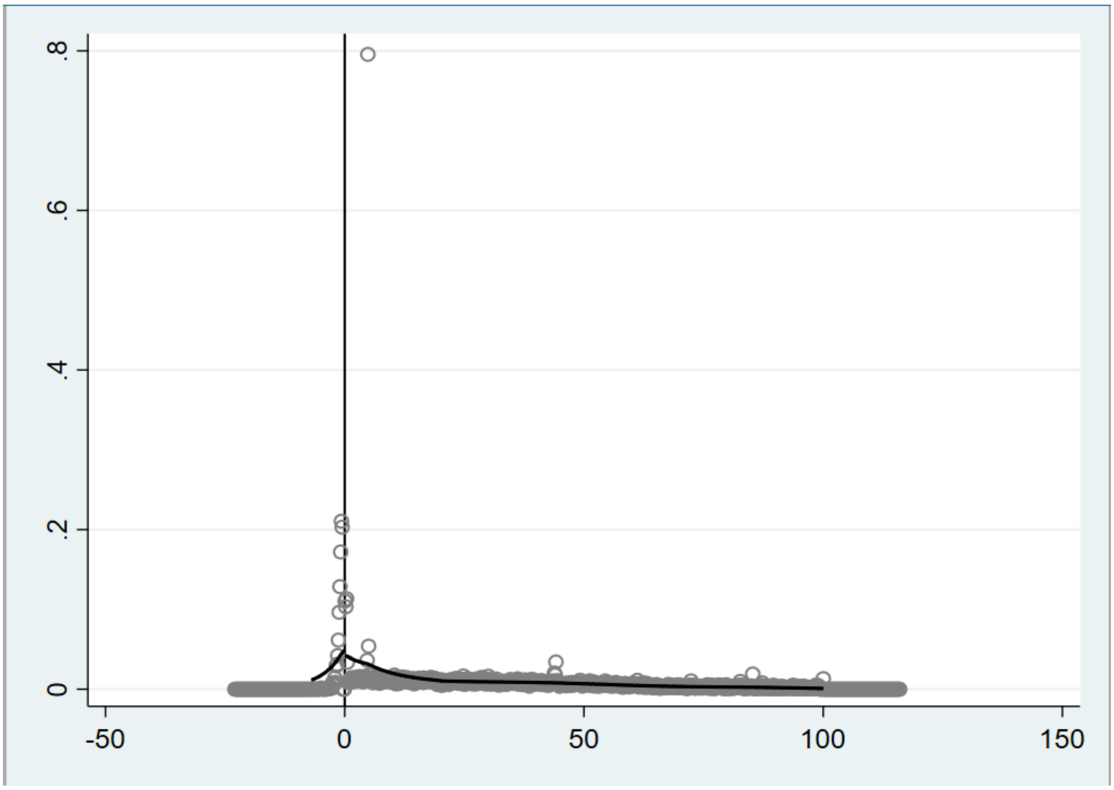

Figure 4-3 Results of Triangle Kernel Function Tests (AsDescribed)

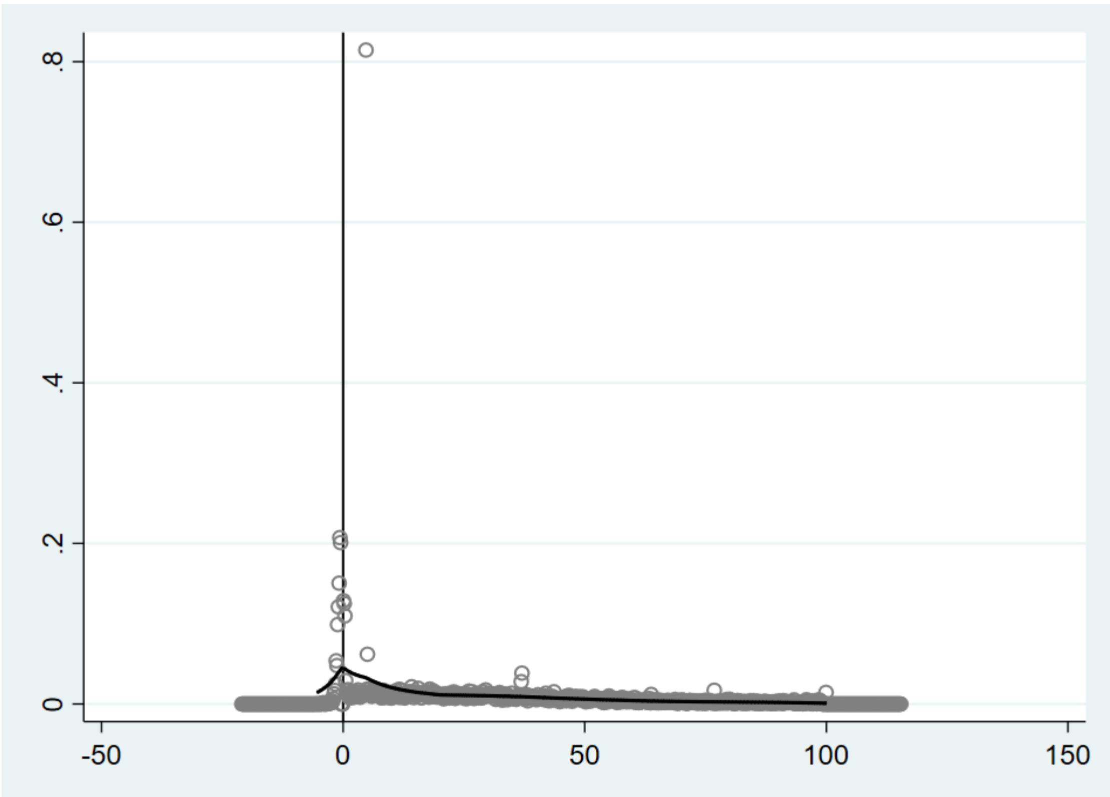

Figure 4-4 Results of Triangle Kernel Function Tests (ServiceQuality)

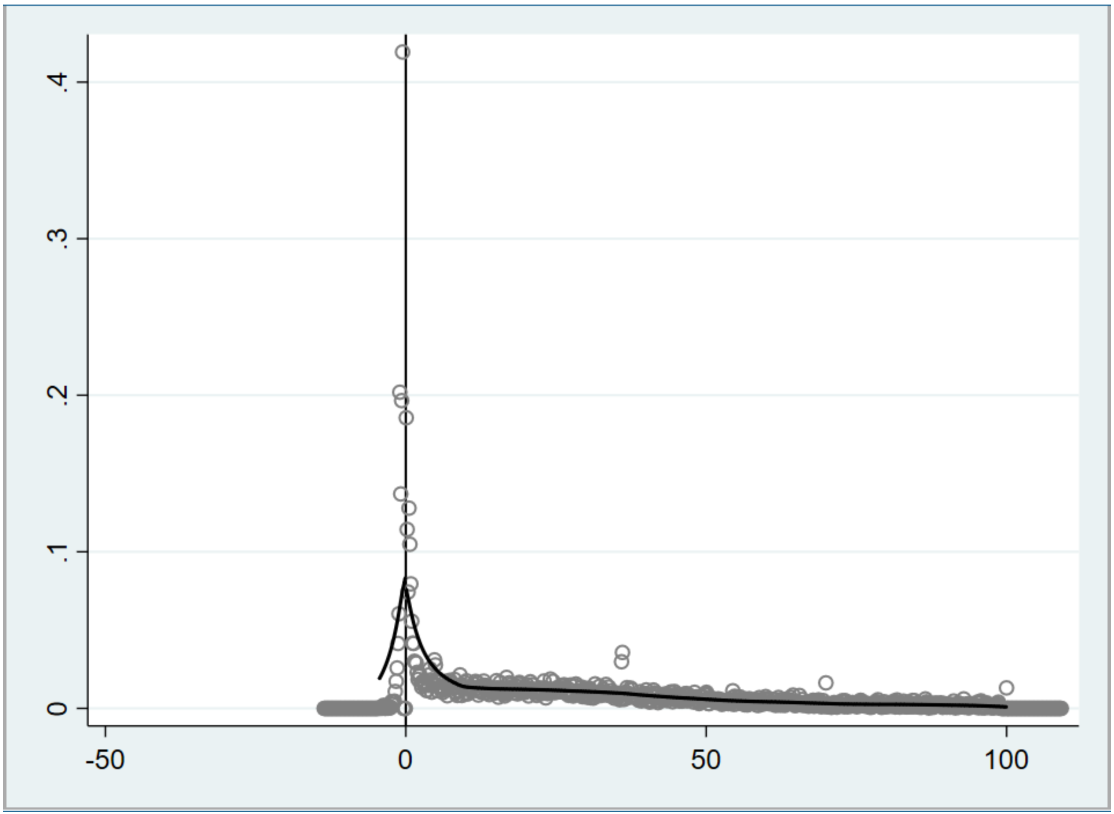

Figure 4-5 Results of Triangle Kernel Function Tests (LogisticsQuality)

(2) Checking continuity in pretreatment covariates

Since RD can be regarded as a local random experiment, the inclusion of covariates does not affect the consistency of the regression discontinuity estimator, but can reduce the variance of the disturbance term and make the estimation more accurate. The validity of the RDD design requires continuity in n pretreatment covariates. If there is also a jump in the conditional density function of the covariates at the cutoff, it is not appropriate to attribute all the LATE estimator to the treatment effect. Therefore, we must first check whether there was any discontinuity in the covariates around the cutoff. Table 4-2 shows that the covariates' RD estimates were not statistically significant, suggesting that the covariates were balanced around the cutoff. Thus, it can be concluded that there is no discontinuity in the covariates around the cutoff.

Table 4-2 RD Estimates to check discontinuity in covariates

Covariates	RD Estimate	P>|z|
SellerID	-1.85013e+10 (-0.38)	0.705
CashbackType	-0.000849 (-0.06)	0.950
DailySales	-67.25(-0.94)	0.348
Accum_time	-0.0217 (-0.08)	0.938
CouponAvailable	-0.00315(-1.05)	0.294
EarnestMoney	0.00498 (1.00)	0.317
ReductionMoney	0.00747 (1.00)	0.317

4.4.2 Causal Impacts of Reputation on Cashback

I first draw a scatter plot to observe whether there is a cutoff point. If there is no obvious jump in the dependent variable at the cutoff, the results of the regression equation may not be significant. However, if I directly draw the scatter plot of all sample points, it will be impossible to observe whether there is a cutoff point because of noise. Therefore, this study first selects some bins, and then calculates the average of outcome variables in each bin, so as to draw a scatter plot. We use the average of outcome variable in each bin and explanatory variable to run the regression on both sides of the cutoff to obtain the fitted value of outcome variable. Then we draw a scatter plot with the fitted value, and connect the scattered points with a smooth curve. In Figure 4-6 to Figure 4-8, the number of bins is defined as50. We make regression analyses on the three reputation variables (AsDescribed, ServiceQuality, and LogisticsQuality) respectively, displaying the scatter plot of the average of outcome variable in each bin and the fitting curve obtained from local linear regression, where the vertical line is the cutoff line. It can be seen from the figure that at the cutoff point, there is an obvious decline in explained variable, which indicates that there may be a causal relationship.

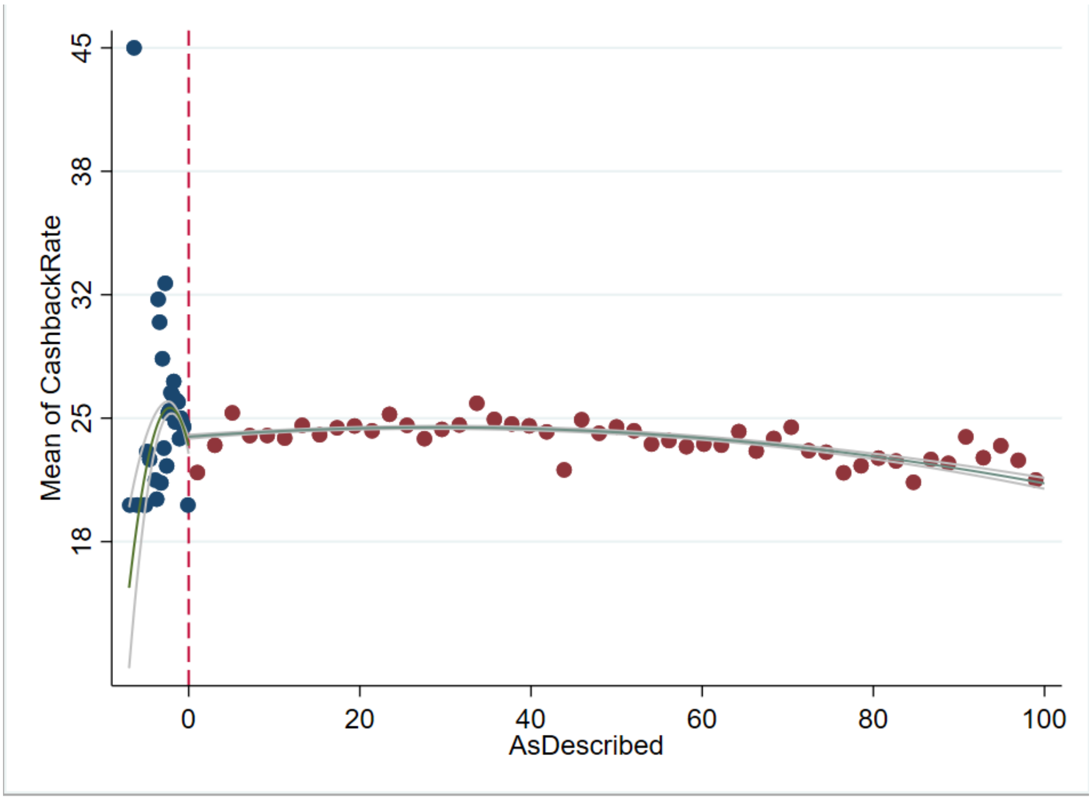

Figure 4-6 RD Plots without Covariates (AsDescribed)

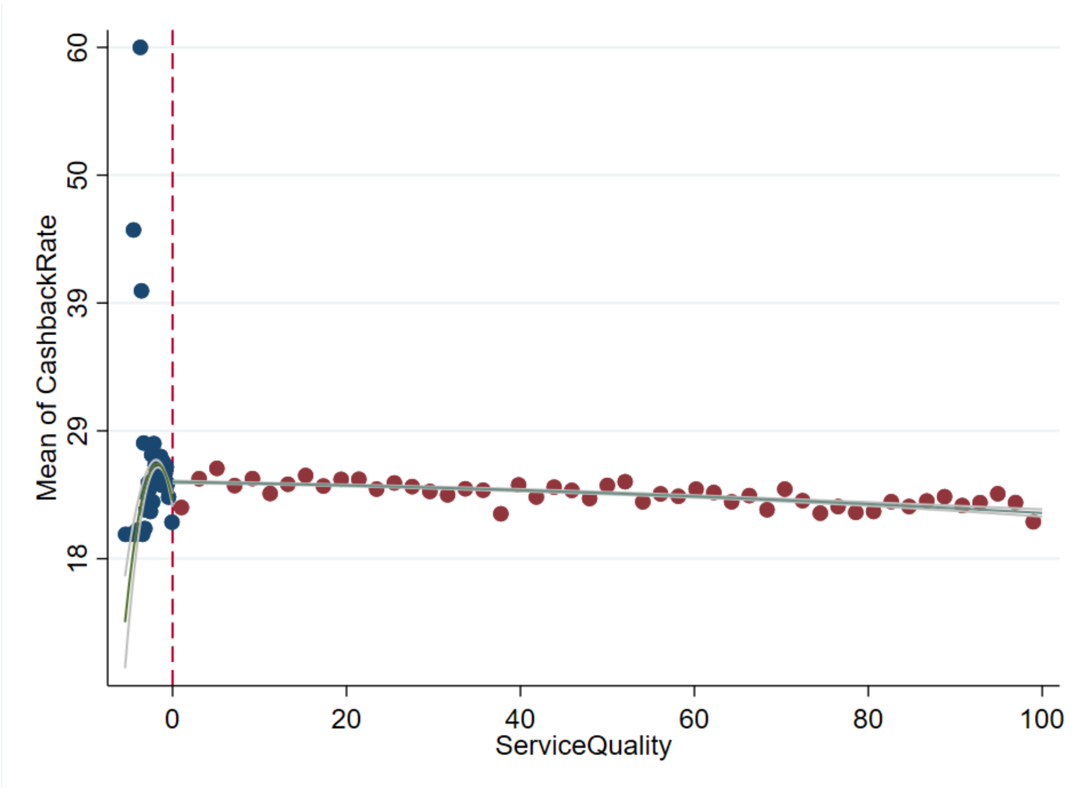

Figure 4-7 RD Plots without Covariates (ServiceQuality)

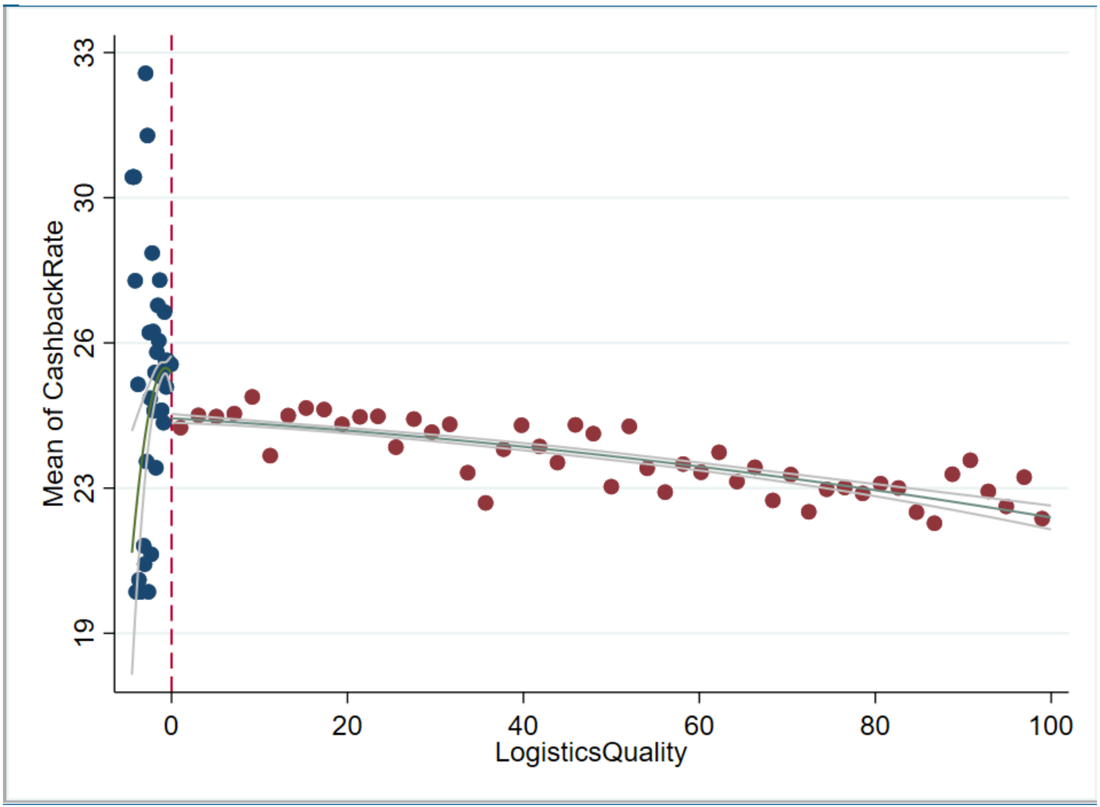

Figure 4-8 RD Plots without Covariates (LogisticsQuality)

Firstly, the optimal broadband and the default triangular kernel are used to run sharp RDD on the three reputation variables respectively. The data show that *AsDescribed* ($b = -2.537$ $p < 0.001$), *ServiceQuality* ($b = -2.455$ $p < 0.001$) and *LogisticsQuality* ($b = -3.536$ $p < 0.001$) and *CashbackRate* have a significant negative effect. When covariates are added, *AsDescribed* ($b = -2.509$ $p < 0.001$), *ServiceQuality* ($b = -2.355$ $p < 0.001$), *LogisticsQuality* ($b = -3.369$ $p < 0.001$), and *CashbackRate* are negative and still significant.

Table 4-3 RD Estimation of Merchant Reputation on Cashback

	No covariates			**covariates included**		
	(1)	(2)	(3)	(4)	(5)	(6)
lwald	-2.537***	-2.455***	-3.536***	-2.509***	-2.355***	-3.369***
	(0.202)	(0.214)	(0.241)	(0.201)	(0.212)	(0.238)
N	111208	111208	111208	111208	111208	111208
R^2						

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Different methods of bandwidth estimation exist in numerous studies (Imbens & Kalyanaraman, 2012; Calonico et al., 2020). In general, researchers will use various bandwidths to evaluate the robustness of their estimates. It is generally believed that the selection of the optimal bandwidth involves a trade-off between bias-variance. On the one hand, a small bandwidth can reduce the risk of model missetting. On the other hand, it also means that the parameter estimation relies on fewer observations, thus increasing the variance (Cattaneo et al., 2020). Valentim, Ruipérez Núñez, A., & Dinas, E. (2021) recommend to report the estimates of non-parametric models at varying bandwidths, both smaller and larger than the optimal one. Ideally, the coefficient will hold regardless of the specific bandwidth size – even if the loss of precision means that, with smaller bandwidths, the results fail to reach statistical significance. In this study, I choose the commonly used 0.5, 1and 2 times bandwidth for analysis.

Combining the regression plots on both sides of the critical point under different bandwidths and the estimated coefficient of LATE, we can see that changes in bandwidth have a small effect on LATE estimate. The regression results show that the three estimates of AsDescribed, ServiceQuality, and LogisticsQuality are all negative. The effects are insignificant only for the variable of ServiceQuality when it is 0.5 times of bandwidth. Therefore, it can be concluded that conditional on covariates, merchant reputation has a negative impact on the cashback level.

Table 4-4 Estimated Coefficients of LATE under Different Bandwidths

	No covariates			covariates included		
	(1)	(2)	(3)	(4)	(5)	(6)
lwald	-2.537***	-2.455***	-3.536***	-2.509***	-2.355***	-3.369***
	(0.202)	(0.214)	(0.241)	(0.201)	(0.212)	(0.238)
lwald50	-3.386***	-0.247	-3.545***	-3.354***	-0.266	-3.094***
	(0.347)	(0.403)	(0.545)	(0.344)	(0.399)	(0.537)
lwald200	-2.545***	-2.520***	-2.505***	-2.518***	-2.422***	-2.386***
	(0.167)	(0.182)	(0.199)	(0.166)	(0.181)	(0.196)
N	111208	111208	111208	111208	111208	111208
R^2						

Standard errors in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.3 Robustness Check

(1) Rectangular kernel regression test

Previously we performed RD estimation using the optimal bandwidth and default triangular kernel. To test the accuracy of the local Wald estimator, we now run a rectangular kernel regression at the optimal bandwidth.

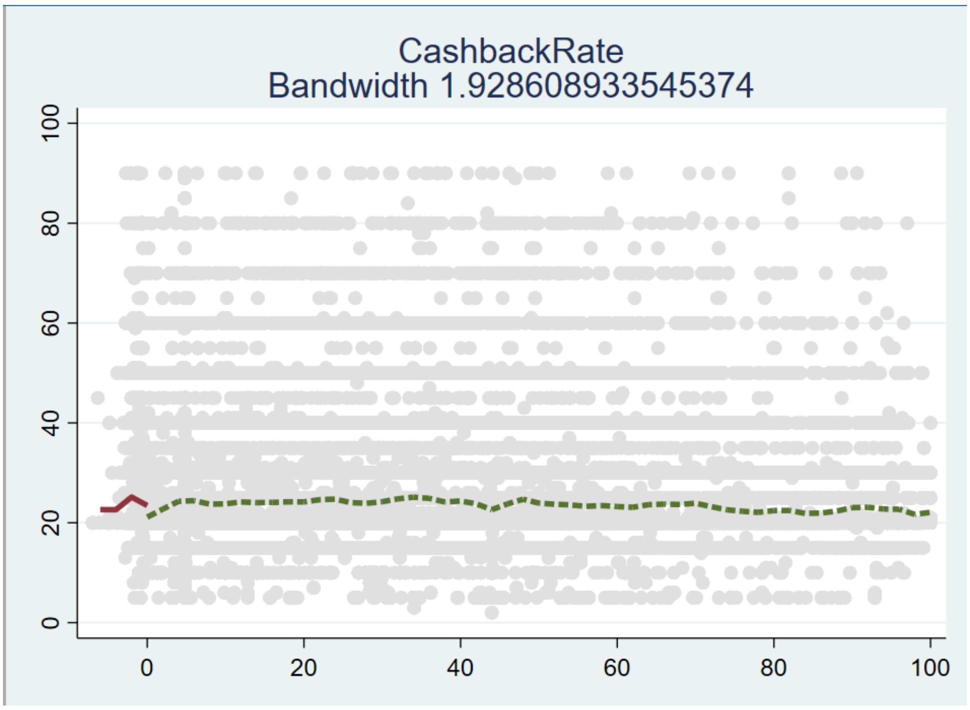

Figure 4-9 Results of Rectangle Kernel Function Tests (AsDescribed)

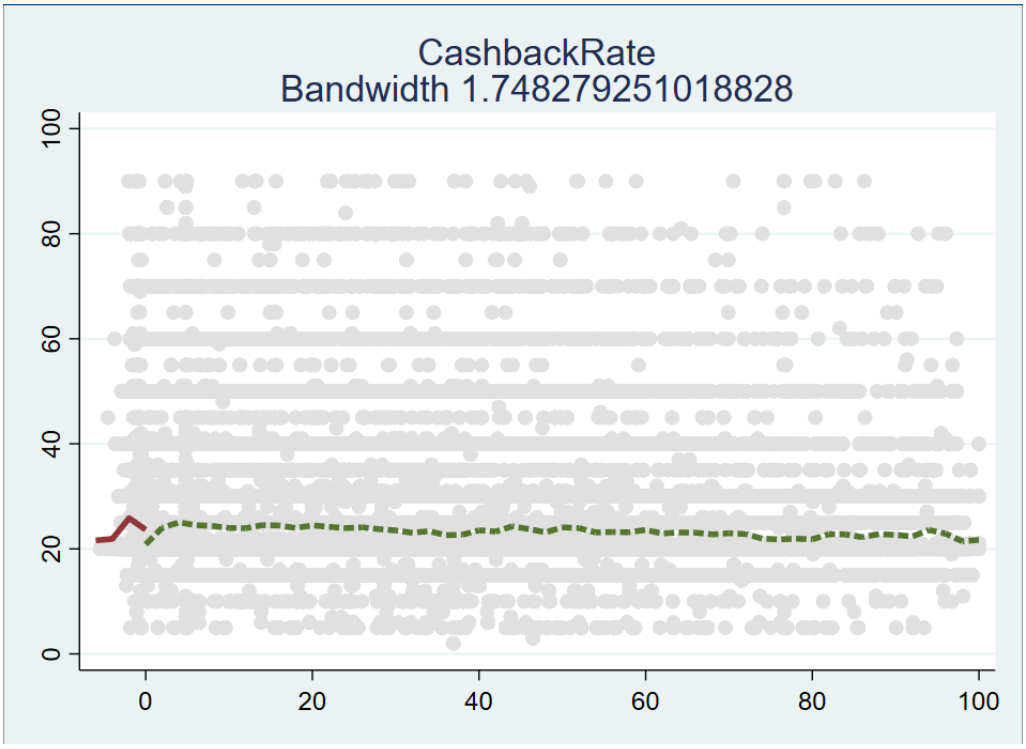

Figure 4-10 Results of Rectangle Kernel Function Tests (ServiceQuality)

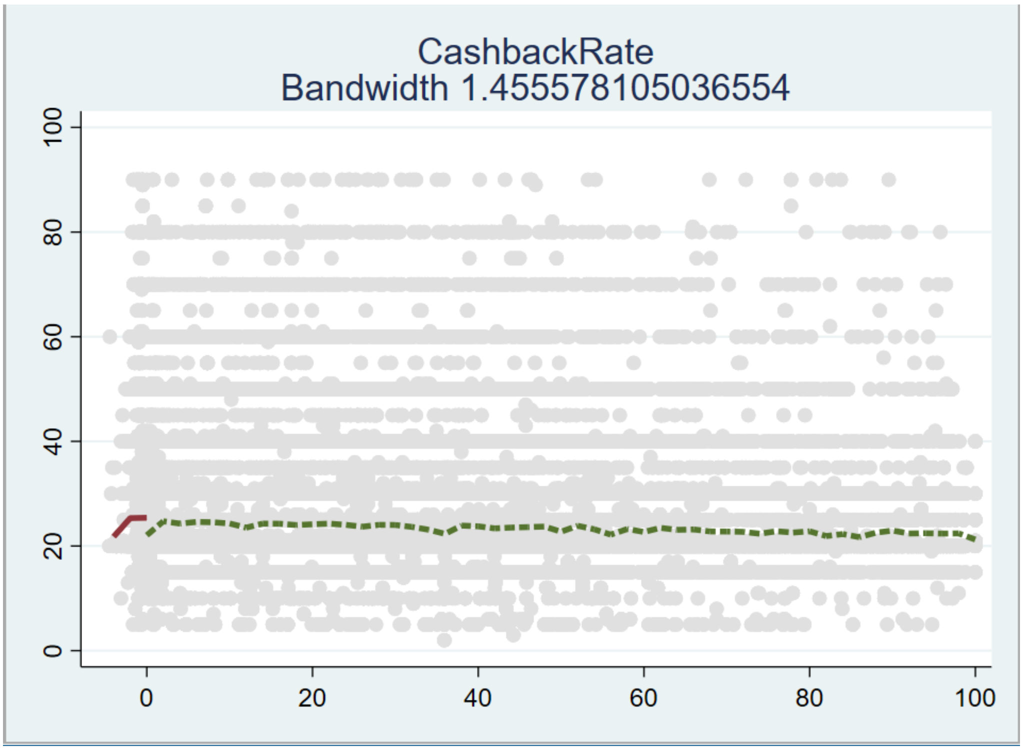

Figure 4-11 Results of Rectangle Kernel Function Tests (LogisticsQuality)

Looking at the regression discontinuity plot of the rectangular kernel, we find that there is still a relatively obvious downward jump. It shows that reputation has a negative effect on cashback. The local Wald estimate of the rectangular kernel is AsDescribed(-2.601)，ServiceQuality（-2.734）, LogisticsQuality（-2.188）, they are all positive and significant compared with AsDescribed(-2.537) , ServiceQuality（-2.455）, LogisticsQuality（-2.536）obtained by the regression of the triangular kernel.

Table 4-5 Results of Rectangle Kernel Function Tests

	(1)	(2)	(3)
	CashbackRate	CashbackRate	CashbackRate
lwald	-2.601***	-2.734***	-2.188***
	(0.168)	(0.182)	(0.197)
N	111208	111208	111208
R^2			

(2) Pseudo cutoff point test

There may exist some unobserved confounding factors in the RD model. For example, the effect of reputation on cashback level around the cutoff point may be caused by jumps of other unobserved confounding factors instead of being completely caused by interventions. To rule out this alternative explanation, a pseudo cutoff point test is performed on the running variables. Specifically, instead of the industry average, other positions of the running variables are used as pseudo cutoff points to calculate RD estimates. This study takes positions on the interval (-1.5, +1.5) around the cutoff as pseudo cutoff points. The results are shown in Table 4-6. The RD estimates of the three reputation variables at the pseudo cutoff points are not significant enough. The results of the pseudo cutoff point test further prove the robustness of RD estimates of all samples.

Table 4-6 RD estimates with placebo cutoffst

	(AsDescribed) -1.5	(AsDescribed) +1.5	(SerciceQuality) -1.5	((SerciceQuality) +1.5	(LogisticsQuality) -1.5	(LogisticsQuality) +1.5
RD_Estimate	-0.614 (-1.82)	0.216 (0.51)	0.197 (0.48)	- -0.282 (-0.35)	0.165 (0.32)	0.556 (1.14)
N	111208	111208	111208	111208	111208	111208
R^2						

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.5 The Moderating Effect of Competition Intensity

This study has included competition intensity as a moderating variable to explore whether competition intensity will affect the original relationship between merchant reputation and cashback level. To measure competition intensity, this paper calculates the number of merchants selling the same product according to product ID. The moderating effect can be tested by including an interaction term between merchant reputation and competition intensity variables. (1), (2) and (3) are the regression results of three reputation variables. The results show that after adding the moderating variable *CompetitionIntensity*, the coefficients rise from -0.008, -0.019, and -0.022 to near 0 respectively, indicating that competition intensity weakens the negative impact of merchant reputation on cashback level, and supports Hypothesis 2.

Table 4-7 Test Results of Moderating Effects of Competition Intensity

	(1) CashbackRate	(2) CashbackRate	(3) CashbackRate
AsDescribed	-0.008***		
	(0.001)		
c.CompetitionIntensity#c.AsDescribed	-0.000***		
	(0.000)		
ServiceQuality		-0.019***	
		(0.001)	
c.CompetitionIntensity#c.ServiceQuality		-0.000***	
		(0.000)	
LogisticsQuality			-0.022***
			(0.001)
c.CompetitionIntensity#c.LogisticsQuality			-0.000***
			(0.000)
_cons	24.292***	24.532***	24.595***
	(0.035)	(0.035)	(0.035)
N	111208	111208	111208
R^2	0.003	0.006	0.008

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.5 Conclusion

This chapter identifies the causal effects of online merchants' reputation on the level of cashback by using discontinuity regression design, and studies the moderating effect of competition intensity between merchants' reputation and cashback level. Our results show that merchants with better reputation are less likely to provide high level of cashback. However, when the competition intensity is high, the impact of merchants' reputation on the cashback level becomes smaller than when the competition intensity is low.

Chapter 5 The Impacts of Cashback on Product Return

5.1 Business Impact of Product Return

Online shopping has brought a lot of convenience and benefits to consumers. However, information asymmetry in online shopping greatly affects the healthy development of e-commerce. One problem faced by many merchants is the issue of product return. The issue of returns is of particular importance for e-tailers as the relative rate of returns for online purchases dwarfs the rate for offline purchases. Specifically, 30% of all products ordered online get returned, compared with 9% bought in brick-and-mortar stores (Zhang &Voorhees, etc., 2022). The information asymmetry between buyers and sellers in the online shopping environment prevents consumers from judging whether the products are suitable for them or not and from identifying product quality in a timely manner, which greatly increases the possibility of consumers being dissatisfied with products and asking for product return (Mukhopadhya & Setaputro, 2004). In addition, services of online shipping need improvement to curb product return. For example, with respect to logistics, the risk of damage to products during carrying, loading, unloading and logistics distribution may affect product and therefore product return. Another example is after-sales service. Ignoring or even having a bad attitude towards consumers' inquiries affects consumers' recognition of the product and leads to high return rate.

Since March 20, 2014, the State Administration for Industry and Commerce has implemented the policy of "returning products purchased online without providing any reason within seven days" for online shopping, which gives consumers more choices and return guarantees, enables them to shop online freely without worry and increases the frequency of product return. At the same time, full return has become the mainstream return strategy of Taobao, JD.com and other shopping platforms, according to which consumers can receive a full refund for products that meet the conditions of non-defective product return. In 2010, the introduction of return shipping insurance effectively solved the problem of return shipping cost, and further lowered the return cost for consumers. Lenient product return policy has double effects on online retailers.

One the one hand, it greatly reduces the risk faced by consumers, allows consumers to shop online more boldly, and leads to a rapid increase in the sales of online retailers; on the other hand, consumers are less tolerant with products, and will return products even if they slightly dislike them, resulting in a surge in product returns (Petersen & Kumar, 2010).

Because a high return rate negatively affects online retailers, major e-commerce platforms have not released specific statistics on the return rate, and merchants are also tight-lipped about it. The return rate calculated by some scholars is incredible due to lack of reliable evidence. However, according to the statistics of America, product return rate of online shopping has always been a serious problem. For example, Saleh (2016) stated that the average return rate of online shopping had reached as high as 22% and was still rising. He also pointed out according to an industry report that at least 30% of products bought online were returned, compared with 8.89% for traditional offline stores. One in three items bought online is returned (Banjo, 2013). The situation is even worse for shoes and fashion products, with more than 50% being returned (Ofek et al, 2011; Flood, 2013).

The increase in product returns has become one of the main problems for online retailers. Manufacturers, distributors and retailers pay high costs in this aspect every year, with profit margins being sharply reduced. The cost for an enterprise to process returns is far higher than the cost of selling those products. Product returns cost American manufacturers and retailers more than $100 billion every year, reducing profits by an average of 3.8% for each retailer or manufacturer (Blanchard, 2007). Retailers whose product return rates exceed 20% often earn zero profit (Janakiraman et al., 2016). A large number of returns, especially those without quality problems, are not only a huge loss for e-commerce, but also a huge waste of social resources (Rao, Rabinovich, & Raju, 2014). Therefore, research on product returns has attracted much attention from both industry and academia.

As a means of promotion, coupons and cashback have significantly improved sales volume, but no scholars have studied the relationship between them and the return rate. This study attempts to compare the effects of coupons and cashback on product return.

5.2 Hypothesis

5.2.1 Effect of Cashback on Return Rate

Loss aversion plays a very important role in consumer behavior. Abdellaoui et al. (2007) proposed various concepts about loss aversion and found strong evidence of loss aversion at both the individual and the aggregate level. Zhao et al. (2010) considered the influence of consumer loss aversion on ordering in advance, and studied whether sellers should sell products in advance and how to maximize the benefits of sales in advance. Blavatsky (2011) extended the concept of loss aversion to more general cases, where the outcome of loss aversion is not measured in money. Research shows that people may tend to choose vague preferences over gambling. Eugene (2011) integrates the previous accounts for pioneering advantage by showing that consumers have higher preferences for the most prototypical and the least uncertain option based on loss aversion and reference dependence effect. Kim & Lee (2014) introduced sellers' profit-maximizing decision under consumer loss aversion and discussed the application of loss aversion in price discrimination and product differentiation.

Although cashback and coupons are both promotion tools, the difference is that the former involves post-purchase behavior and the latter involves pre-purchase behavior. Cashback is post-purchase, and the cashbacks obtained after buying the product give consumers a sense of ownership. If the product is to be returned, it means that the cashbacks in the account will also be returned. Meanwhile, customers fear that they may not be able to buy the product at such a cheap price after returning it. The fear of loss makes consumers tend to maintain the status quo rather than make a change and return the product.

Hypothesis1: Cashback level has a negative impact on product return rate.

5.2.2 Effects of Coupons on Return Rate

Coupons are a powerful marketing tool that can stimulate the sales of slow sellers and boost sales of new products (Kotler et al., 2013; Taylor, 2001). Narasimhan (1988) proposed that coupons can provide relatively low prices for specific consumer groups. Dhar & Hoch (1996) found that in-store coupons can bring higher sales and profits than purchase bonuses (discounts) after comparing coupons and discounts. Compared with purchase bonuses, in-store coupons had an average redemption rate of 55%, increased sales of promotional brands by 35%, and improved profits in dollars by 108%. Chen & Lou (1998) focused on two promotion tools, i.e., discounts and coupons, to study whether they affect consumers' purchase intention. If merchants use coupons for sales promotion, they can have a bigger influence on consumers' purchasing intention. Compared with discount promotions, coupons often need to be used within a certain time range, which requires consumers to make a purchase within the validity period of coupons. This will bring time pressure and make customers believe that they will lose the chance for a discount if they do not use coupons. In this sense, usage of coupons can increase consumers' purchase intention. Laroche (2003) compared coupons with the offer of buying one and getting one free (BOGO), and found that if merchants use coupons for promotion, consumers are more inclined to buy and store products for later use during the validity period of coupons. But if merchants adopt BOGO, consumers' purchase intentions decline compared with coupon promotions.

Since price promotion can sharply increase product sales, the price plays a driving role in impulsive consumption. Robertson (1978) and Zhou & Wong (2003) found that the lower the product price, the more it can stimulate impulse purchase. In fact, online promotion is also a marketing stimulation method often adopted by online e-commerce merchants to enhance purchase intention of online consumers. Currently, most of the coupons used on various platforms are money-off coupons. Coupled with policies such as free product return and return insurance, they further stimulate consumers to add on items and buy many products that they do not really need. Meyer (1990) found that the bigger the price discount of a product is, the more likely the consumers are to make impulse purchase and excessive purchase. Impulsive purchase often leads to post-purchase regret. The more impulse the consumers are when making the purchase, the more regretful they are after the purchase. Regret always comes with reflections on mistakes and missed opportunities, and with the eager to complain about themselves, correct mistakes, get things back as they were, get a second chance and act immediately if given the chance. So, one of the core components of a regretful experience is the desire to cancel the decision that leads to regrettable outcomes (Cases, 2002). The sense of gain brought by coupons used before purchase will disappear after purchase, but the regret caused by impulsive consumption will occupy consumers' brain and cause them to correct his mistake by returning the product. Product return is a way to offset post-purchase regret by changing the purchase decision that leads to negative outcomes. Based on the above analysis, Hypothesis 2 is proposed as follows,

Hypothesis 2: Coupons have a positive influence on product return rate.

5.2.3 Moderating Effect of Merchant Reputation

Online merchant reputation refers to the level of consumer trust in the integrity of platform merchants and the level of attention they receive (Koufaris & Hampton-Sosa, 2004). On e-commerce platforms, higher seller reputation generates a higher degree of initial trust in consumers. According to the initial trust theory (McKnight, Cummings, & Chervany, 1998), a higher level of initial trust affects consumers' behavioral intention. Thorelli & Ye (1989) argued that positive seller reputation can increase consumers' trust in the products they buy. Jarvenpaa et al. (1999) believed that the reputation of e-commerce platforms has a positive effect on the level of consumers' initial trust. On this basis, Walsh et al. (2016) built a model of influence of online retailer reputation on return rate and showed that online retailer reputation has a significant negative effect on return rate. In the context of e-commerce platforms, higher seller reputation can improve buyers' trust in products, thereby reducing their willingness to return products. Therefore, I hypothesize that:

Hypothesis 3a: The influence of cashback on return rate is smaller with high merchant reputation than that with low merchant reputation.

Hypothesis3b: The influence of coupon on return rate is smaller with high merchant reputation than that with low merchant reputation.

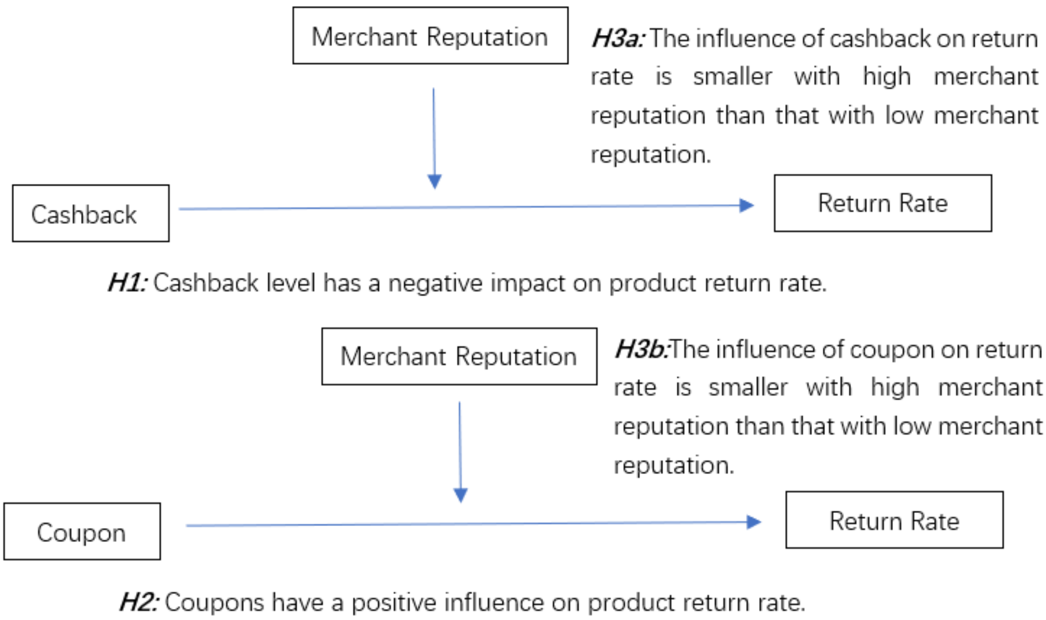

Figure 5-1 Figure Theoretical Model for Study 2

5.3 Research Design

5.3.1 Sample Description

Transaction data in Study 2 comes from the same large cashback platform. This paper extracts user transaction information on the platform from October 30, 2020 to November 12, 2020, grabs merchant status information from Taobao through crawler, and obtains information of 19,538 orders on 8,359 products from 4,826 merchants by matching with product ID.

Dependent variable: $ProductReturn_{ijk}$: is a 0/1 variable. It is 1 if the k^{th} order for product j sold by merchant i is invalid; otherwise, it is 0. Use this variable to indicate whether the current order is subject to a product return order.

Independent variables: $Cashback_{ij}$ i is directly used to measure the cashback associated with the item, because there is no specific amount of cashback in the database, but users can directly learn the annualized revenue of the purchase of the item on the product interface. The expected annualized return is determined according to the amount of commission, so the amount of commission is used as the proxy variable for cash back. Another independent variable is $CouponValue_{ij}$. Taobao merchants offer various forms of coupons, among which the most used is the coupon offered when spending is over certain amount. For example, you can get 20 Yuan discount for spending over 200 Yuan. With these deals, your coupons get a certain discount once they reach a minimum amount. The minimum spending coupon is one of the most simply yet effective ways to increase sales. This study lacks the form of specific coupons, only the value of discount obtained for each order, so the types of coupons are not distinguished in my study.

Moderating variable: The moderating variable is *GoldSeller*, which is used to measure reputation. Gold sellers are an official incentive for sellers with good sales, good service and good reputation within a period of time. Taobao uses data to evaluate and mark the sellers. For sellers, GoldSeller is a kind of honor and recognition. For buyers, GoldSeller help reduce the cost of shopping decisions.

Control variables: *CashbackType* is the types of cashbacks, includes four types: General, Targeted, High cashback and RuyiTou. $ShopType_{ij}$represents the category of the stores. $ShopLevel_{ij}$is the level of the seller of the product. $AsDescribed_{ij}$ is percentage measure of the description score. $ServiceQuality_{ij}$ is percentage measure of the Service attitude score. $LogisticsQualityt_{ij}$ is percentage measure of the logistics service score. $Brand_i$ indicates whether the good is a brand or not. $FreightInsurance_{ij}$ indicates whether the buyer has taken out freight insurance. $FreeshipRemoteDistrict_{ij}$ indicates whether buyers can get free shipping. . $CouponNum_{ij}$ is total number of coupons issued. $CouponReceiveNum_i$ refers to the total number of coupons currently being received. $ClassID_j$ refers to the classification of goods. $sellerID_j$ refers to the ID of sellers, which are unique identifiers.

Table 5-1Table Description of Variables

变量名	定义	Mean	Std. Dev.	Min	Max
ProductReturn	The order of return	0.114	0.318	0	1
Cashback	The value of Cashback	5.327592	10.68389	0	432
CouponValue	The value of coupon	17.27654	39.48361	1	1000
GoldSeller	1 -Yes, 0 -non-gold seller	0.0250	0.156	0	1
CashbackType	0- General, 1- Targeted , 2- High cashback, 3- RuyiTou	2.993858	.1274327	0	3
ShopType	1-Tmall，0-TaoBao	0.967	0.179	0	1
ShopLevel	Taobao Shop Level	16.54	2.716	0	20
AsDescribed	Percent on the description score	17.71	17.57	-4.480	98.56
ServiceQuality	Percent on the Service attitude score	14.50	15.08	-4.320	97.80
LogisticsQuality	Percent on the Logistics service score	22.79426	25.32076	-4.5	99.99
CouponNum	Total number of coupons issued	100517	163406	550	5000000
CouponReceiveNum	The total amount of coupons claimed	5231	31969	0	1365000
FreightInsurance	0- no freight insurance, 1- freight insurance	0.527	0.499	0	1
FreeshipRemoteDistrict	0- no free shipping, 1- free shipping	0.330	0.470	0	1
ClassID	1, women's clothing, 2, Mather-baby......	4.97661	2.544343	1	14
SellerID	The ID of sellers	2474.961	1361.044	0	4825

Note. number of observations is 19，538

5.3.2 Empirical Models

The data used in this study are panel data, which are usually analyzed using fixed-effects models or random-effects models. Under fixed-effects models, differences across individuals are fixed at different time, thus effectively excluding the influence of omitted variables on dependent variable and the interference effect on the relationship between independent variable and dependent variable. Fixed-effects models can solve the problem of biased estimate caused by omitted variables to some extent. The main difference between them is that fixed-effects models treat unobserved differences between individuals as fixed parameters, while random-effects models treat omitted variables as random variables with a special probability distribution, and assume that they are uncorrelated to observed variables. It is often hard to satisfy such an assumption because omitted variables are often correlated to other explanatory variables in the model.

This paper chooses fixed-effects models to analyze sample data, and uses SellerID to conduct cluster analysis and study the influence of coupons and cashbacks on return rates. The empirical model is as follows:

$$ProductReturn_{ijk}=\beta_0+ \beta_1 Cashback_{ij}+\beta_2 CouponValue_i+\beta_3 Cashback_{ij}* GoldSeller_{ij}+\beta_4 CouponValue_{ij}* GoldSeller_{ij}+ \beta_5 GoldSeller_{ij}+\beta_6 Controls_{ij}+ SellerRE_i+\sigma_{ij}$$

Among them, $ProductReturn_{ijk}$ is a dummy variable. A value of 1 indicates that the order is a return order, otherwise, it is 0. The interaction term reflects the influence of merchant reputation on the relationship between cashbacks and coupon and return rates. $Controls_{ij}$ represents all control variables. $SellerRE_i$ represents the individual fixed effect of merchant i, while σ_{ij} represents the error term.

5.4 Empirical Analysis

5.4.1Empirical model selection

(1) LSDV Test

Least Square Dummy Variables (LSDV) model allows for heterogeneity among subjects by allowing each entity to have its own intercept value. From Table 5-2, Through the LSDV test, it can be concluded that for the remaining 13 dummy variables of product classification with women's clothing as the reference, the P values of the product classification variables in most regions are significant within the 5% significance level, so the null hypothesis Ho "all dummy variables of product classification are 0" can be rejected, and the alternative hypothesis of individual effect is accepted. It is shows that there are individual effects and mixed regression should not be used.

Table 5-2 The result of LSDV Test

Dummy variable	**Coef.**	**P>|t|**	**Dummy variable**	**Coef.**	**P>|t|**
Mother-baby	-.0920529	0.003	Men's Clothing	-.0384007	-0.87
Beauty Products	-.0690054	0.024	Underwear	-.0954653	0.003
Daily Necessities	-.0690054	0.001	Luggage	.0067317	0.10
Shoes	-.0361745	-0.76	Accessories	-.0875322	0.022
Food	-.0691391	0.024	Outdoor Sports	-.0705787	0.097
Recreational Goods	-.0954767	0.004	Home Textile	-.0553875	0.181
Consumer Electronics	-.0745377	0.023			

(2) Hausman Test

The results in Table 5-2 prove the existence of individual effect, but the individual effect can exist in the form of random effect and fixed effect. When dealing with panel data, the Hausman test is needed to determine which one to use. Hausman test is used in testing for the cause- effect relationship between the dependent and independent variables in a model**.** If the P value is significant, fixed effect should be used but if the value is not significant, the random effect should be used.

Table 5-3 The result of Hausman Test

Test: Ho: difference in coefficients not systematic
chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 175.81
P = 0.0000

According to the Hausman test of the fixed effect model and the random effect model in Table 5-3, the P value of the Hausman test is 0.0000 at the significance level of 5%, so the null hypothesis is strongly rejected. A fixed effects model should be used to study the effect of cashback and coupon value on the product return.

5.4.2 Analysis Results of Fixed-Effects Model

Model 1 in Table 5-4 shows the main effects of merchant cashbacks and coupons on product return. The data show that cashback has a negative effect on product return(($b = -0.006$ $p < 0.01$), while coupon value has a positive effect on product return（$b = 0.001$, $p<0.01$）. The moderating roles of seller reputation (a gold seller or not) on the main effects mentioned above has been verified in the regression. The data show that after including the reputation interaction item, the coefficient of merchant cashbacks on return rate becomes larger in absolute value ($b = -0.010$, $p<0.01$), indicating that reputation improves the effects of merchant cashbacks on return rate and further lowers return rate. Meanwhile, the results also show that the relationship between coupons and return rates（$b = 0.002$, $p<0.01$）has been stronger when reputation is high, further increasing consumers' tendency to return product. This finding differs from Hypothesis 4. One possible explanation is that high reputation boosts impulsive spending caused by coupons, further increasing the return rate.

Model 2 in Table 5-4 is the regression results when sellers fixed effects are added. The data show that cashback has a negative effect on product return(($b = -0.009$ $p < 0.01$), while coupon value has a positive effect on product return（$b = 0.000$, $p<0.15$）. The higher the cashback, the lower the return rate ($b = -0.028$ $p < 0.01$). However, the moderating effect of *GoldSellesr* on *CouponValue* and *ProductReturn* is not significant. This indicates that merchant reputation does not have a moderating effect in the relationship between coupons and return rate.

Table 5-4 Regression Results of OLS and Fixed-Effects Model

	(1)	(2)
	ProductReturn	ProductReturn
Cashback	-0.006***	-0.009***
	(0.000)	(0.002)
CouponValue	0.001***	0.000+
	(0.000)	(0.000)
c.GoldSeller#c. Cashback	-0.010***	-0.028**
	(0.003)	(0.010)
c.GoldSeller#c.CouponValue	0.002***	0.002
	(0.001)	(0.022)
GoodsPrice	0.000***	0.000***
	(0.000)	(0.000)
CashbackType	-0.000	-0.000
	(0.000)	(0.000)
CouponNum	0.000*	0.000
	(0.000)	(0.000)
CouponReceiveNum	0.028***	-0.018
	(0.005)	(0.018)
FreightInsurance	0.020***	0.007
	(0.005)	(0.011)
FreeshipRemoteDistrict	0.014	0.004
	(0.017)	(0.022)
GoldSeller	-0.003***	0.006
	(0.001)	(0.055)
ShopLevel	-0.001*	0.001
	(0.000)	(0.005)
AsDescribed	-0.000	-0.010*
	(0.001)	(0.005)
ServiceQuality	0.001*	0.012*
	(0.000)	(0.006)
LogisticsQuality	0.001	0.004
	(0.001)	(0.003)
ClassID		0.034
		(0.021)
_cons	0.160***	-0.092
	(0.016)	(0.910)
N	19538	19538
R^2	0.047	0.063

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10, + p<0.15

5.4.3Heterogeneity Analysis

This study has also examined the heterogeneity among different kinds of products. On the basis of the original model, the dummy variables of goods category in *ClassID* are used to form interaction terms with Cashback and CouponValue respective to identify the heterogeneous effects. The results show that cashbacks have negative effects on all kinds of products and has the greatest negative impact on women's clothing, men's clothing, underwear, shoes, outdoor sports, because these goods belong to the clothing category, has always been the highest return rate.

In contrast, coupons have positive effects on product returns. From the results, luggage and accessories are most affected by coupons discount, probably because compared with clothing, these goods are non-essential goods, and the use of coupons leads to more impulse buying and post-purchase regret, so buyers will be more inclined to return the goods.

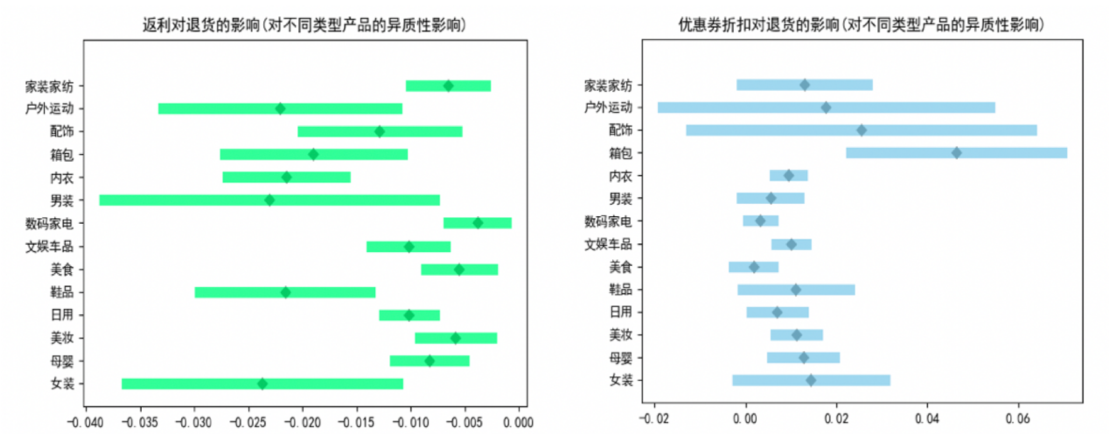

Figure 5-2 Coefficient of Different Kinds of Products

5.4.4Robustness Check

(1) Random -Effects Model Test

In order to test the robustness of the results, the random effects model is used to test the results again. The data show that the higher the cashback, the lower the return rate (b = -0.00637, p < 0.01). On the contrary, the higher the coupon value, the higher the return rate ($b=0.00617$, $p<0.01$). The coefficient of merchant cashback on return rate becomes larger in absolute value ($b = -0.0103$, $p<0.01$), indicating that reputation improves the effects of merchant cashbacks on return rate and further lowers return rate. The relationship between coupons and return rates（$b = 0.0251$, $p<0.01$）is stronger when reputation is high, further increasing a consumer’s tendency to return product. The regression results are the same as those of fixed effects models， and the robustness of the regression results is proved.

Table 5-5 Regression Results of Random -Effects Model Tests

VARIABLES	ProductReturn
Cashback	-0.00637***
	(0.000958)
c.GoldSeller#c.Cashback	-0.0103***
	(0.00373)
CouponValue	0.00617***
	(0.00102)
c.GoldSeller#c.CouponValue	0.0251***
	(0.00776)
GoodsPrice	1.42e-05
	(1.27e-05)
CouponNum	1.29e-05
	(1.86e-05)
Brand	0.0176***
	(0.00665)
FreightInsurance	0.0260***
	(0.00577)
Freeshipremotedistrict	0.0213***
	(0.00615)
GoldSeller	0.0158
	(0.0326)
Shoptype	-0.00438
	(0.0248)
Shoplevel	-0.00532***
	(0.00115)
AsdecribedUP	0.0113
	(0.0121)
ServiceQualityUP	-0.0171
	(0.0128)
LogisticsQulityUP	0.00391
	(0.00813)
Classid	0.000963
	(0.00115)
Order_Dateid	0.000623
	(0.000926)
Constant	0.189***
	(0.0328)
Observations	19,538
Number of SellerID	4,826

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

(2) Time Fixed Effects Model test

In order to further verify the robustness of regression results, this study performs regression analysis again after adding the time fixed effects. In this study, a total of 14 consecutive days of order data were intercepted. Based on the time when the order was generated, I created a dummy variable *OrderDat*e. *OrderDate* contains a total of 14 observations from 1 to 14.

The data show that the higher the cashback, the lower the return rate (b = -0.00637, p < 0.01). On the contrary, the higher the coupon value, the higher the return rate (b=0.00621, p <0.01). The coefficient of merchant cashbacks on return rate becomes larger in absolute value (b = -0.0103, p<0.01), indicating that reputation improves the effects of merchant cashbacks on return rate and further lowers return rate. The robustness of the regression results is proved again.

Table 5-6 Regression Results for Time Fixed effects Model

VARIABLES	ProductReturn
Cashback	-0.00637***
	(0.000220)
GoldSeller*Cashback	-0.0103***
	(0.00255)
CouponValue	0.00621***
	(0.000592)
c.GoldSeller#c.CouponValue	0.0252***
	(0.00682)
GoodsPrice	1.41e-05***
	(2.95e-06)
CouponNum	1.38e-05
	(1.39e-05)
Brand	0.0178***
	(0.00536)
FreightInsurance	0.0254***
	(0.00467)
Freeshipremotedistrict	0.0211***
	(0.00506)
GoldSeller	0.0154
	(0.0298)
Shoptype	-0.00529

	(0.0250)
Shoplevel	-0.00553***
	(0.000986)
AsdecribedUP	0.0111
	(0.00885)
ServiceQualityUP	-0.0169*
	(0.0101)
LogisticsQulityUP	0.00370
	(0.00747)
ClassID	0.000993
	(0.000892)
OrderDateid	0.198***
	(0.0300)
Observations	19,538
Number of Orderdate	14
R-squared	0.047

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

5.5 Conclusion

This chapter investigates the impacts of cashbacks on product return. Moreover, we compared the effects with those of coupon discount and discussed the moderating effect of merchant reputation. The results show that although coupon discount has a positive effect on the product return rate, the cashback level has a negative effect on the product return rate. The impact of cashback on the product return rate is moderated by the reputation of the seller. For merchants with high reputation, the inhibition effect of cashback level on return rate is stronger. However, the moderating effect of reputation on the relationship between coupons and return rate is not significant.

Chapter 6 Discussion

This dissertation takes Taobao merchants on a large cashback website in China as the research object, and mainly studies the impacts of reputation on cashback and the impacts of coupon discounts and rebates on the cashback rate. The following conclusions are drawn from the study:

(1) Merchants' reputation has a significant negative effect on the level of cashback and is moderated by the intensity of competition. When the competition intensity is high, the impact of merchants' reputation on the cashback level becomes smaller than when the competition intensity is low.

(2) The coupon discount has a positive effect on the product return rate, while the cash level has a negative effect on the rate of return. Cashback levels have a stronger dampening effect on return rates for sellers with high reputation, However, the moderating effect of reputation on the relationship between coupons and return rate is not significant.

6.1 Theoretical Contribution

This dissertation has made several theoretical contributions to e-commerce research.

First, it collected huge volume of transaction-level sales data for empirical analysis. This differs from other empirical research that uses questionnaires or experiments to obtain relevant data. An important advantage of this study is that we cooperated with a large cashback website. Under the premise of keeping user information confidential, we obtained in-depth data directly from the research partner through big data collection. This unique opportunity enabled us to collect dozens of relevant variables such as the sale price, coupon, cashback amount, and merchant reputation when the order was placed. The rich data set provides a sound basis for our empirical analysis, which outperforms previous relevant studies.

Second, based on the data advantages, we empirically analyzed the effects of merchant reputation on cashback level through the panel data of merchant reputation, and proved that online merchant reputation has significant negative impacts on cashbacks. At the same time, we studied the moderating effects of competition intensity on the merchant reputation and cashbacks. Our study broadened the research scope of online reputation research and further enriched the reputation theories.

Third, leveraging on 111,199 transaction records from a large cashback website and RDD, we employed a non-parametric method to estimate causal effects of online merchant reputation of service providers on cashback level. The study creatively used the industry average of dynamic ranking on Taobao as a cutoff point in the RD design, successfully addressed the endogeneity concern and demonstrated a causal relationship between reputation and cashback level.

Fourth, the study compared the effects of coupons and cashbacks on return rates. Previous studies often only consider one promotion method and study its effect on sales. However, different promotion methods can not only affect sales, but also affect return rates differently. Empirical analysis in this paper showed that effects of the two promotion methods on return rates are opposite. Coupons increase products return rates, but cashbacks lower them.

Fifth, previous research on the influencing factors of product returns mainly focused on defects in products or services and return policies. This paper examined different promotion methods and investigated the relationship between e-coupons, cashbacks and product returns. It extended loss aversion theory from the study of purchase behavior to the study of return behavior, interpreted product returns from a new perspective, expanded the applicable fields of loss aversion theory, and provided a useful complement to the research on product return.

6.2 Practical Implications

In recent years, with the vigorous development of e-commerce, various online promotion methods have emerged. Among them, cashback promotion has become increasingly popular as one of the mainstream online promotion methods. Cashback websites first appeared in America in 2000. The first cashback website in China was established in 2006, but it was not until the joining of the two Internet giants Tencent and NetEase in 2009 that people gradually knew cashback websites and began to use them. After that, cashback websites ushered in a period of golden development, during which 51fanli.com, QQ cashback, NetEase cashback, egou.com and 51bi were established successively. The rapid development over the last ten years shows that the new e-commerce model of cashback websites can meet market demand and has significant growth potential. However, the rise of a large number of cashback websites has intensified industry competition.

At the same time, research on cashbacks has begun to increase. Focusing on the relationship between cashbacks and consumer behavior, this paper studied the relationship between merchant reputation and cashback level on a cashback shopping website and compared the effects of coupons and cashbacks on return rate. The research results provide useful guidance for merchants to optimize the cashback strategy and make sound cashback decisions under fierce market competition. .

First, this dissertation took Taobao merchants on a large Chinese cashback platform as research subjects, collected a large amount of original transaction data for empirical analysis, and focused on the relationship between merchant reputation and cashback. Through regression discontinuity analysis, we find that there is a significant negative correlation between merchant reputation and cashback level, which is moderated by competition intensity. The conclusion shows that merchants with a good reputation can appropriately lower the cashback level, while merchants that have not yet established a good reputation need to increase the cashback level appropriately when using cashback for promotion. The study also finds that competition intensity plays a moderating role between reputation and cashback level, namely, fierce competition in the sold products increases the cashback level, and less fierce competition lowers the cashback level. Therefore, online merchants can also appropriately moderate the cashback level based on the level of product competition on the platform.

Second, the problem of product return in online shopping has always been a headache for online retailers. Lenient return policies result in high return rates for online shopping, which continuously erodes the profits of online retailers, and makes it difficult for small and medium-sized retailers to maintain operation. Reverse logistics of product return also causes waste of manpower, materials and resources. Therefore, it is of profound practical significance to lower the return rate of online shopping. This paper adopts fixed effects model to compare the effects of coupons and cashbacks on return rate. The empirical analysis results show that the deeper the coupon discounts, the higher the return rate. However, the higher the cashback level, the lower the return rate. Therefore, when online merchants launch product promotions in consideration of return rate, they need to balance the relationship between cashbacks and coupons. The study also evaluates seller reputation according to "whether it is a gold seller or not" and examines the moderating effects of reputation on the main effects mentioned above. The results show that reputation improves the effects of merchant cashbacks on return rate and further lowers return rate. Therefore, for sellers with a good reputation, the promotion results of increasing cashback level are much better than those of coupons. The findings inform sellers that it is not advisable to blindly increase sales. Only by providing truly valuable products for consumers and meeting their real needs can the return rate be effectively lowered.

6.3 Limitations and Future Research

Although this paper has made unique contributions to both theory and practice, there are still some limitations. We hope that future research will improve in the following aspects.

First, this paper mainly took Taobao merchants on the cashback platform as research objects, and thus we ignore the merchants that hadn't launched cashback promotions. Besides, the consumers in the study were interested in cashbacks and could be seen as price-sensitive consumers. Therefore, the conclusions of this paper may not be applicable to all sellers and consumers on the e-commerce platform.

Second, this paper only selected competition intensity as the moderating variable. However, there are many factors that affect the cashback level, and there must be other moderating variables or these factors may have mediating effects. Future research can make more explorations in this aspect, enrich and supplement the research results, and improve the application value of the research.

Third, in addition to coupons and cashbacks, various other promotion methods are available for online merchants. For example, purchase limits, cashback coupons and cashbacks for positive review may also affect the product return rate. Future research may consider these alternative promotions methods.

Finally, since the cashback platforms adopt deferred payment and the design is very complicated, we were unable to obtain actual cashback amount received by consumers directly. Instead, considering that cashback platforms often give a certain percentage of commission obtained from merchants back to consumers, we replace the cashbacks received by consumers with commissions of online merchants. Future research may obtain detailed consumer level cashback data to study the effect of cashback on consumer behavior.

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