Article

How Online Reviews Affect Consumer's Quality Belief: Ex-Ante and Ex-Post Preference of Consumption Decision

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Abstract
Although many studies investigate the impact of online reviews on sales, much fewer investigate consumer satisfaction following the purchasing decision. I hypothesised that online reviews would have an impact on both sales and product returns. I developed an analytical model that demonstrates how risk-neutral reference-dependent consumers form a pre-consumption quality belief and a post-consumption consumption utility. I empirically tested the hypothesis using a cross-sectional data set collected from Taobao.com. By controlling for the effect of product type, and adding monetary incentives (in return for leaving positive reviews) as the instrumental variable for positive review rates, I ran 2SLS regressions of sales and returns on reviews. The result supports the proposition that the positive review rate is positively associated with both returns and sales, while the negative review rate is negatively associated with both returns and sales. Consumers tend to overestimate true product quality with positive reviews, while negative reviews tend to be more informative about the true quality of products. This is because sellers generally manipulate positive reviews and ratings to attract potential buyers. The result suggests that consumers could discount their quality beliefs before making the purchasing decision. This would increase the reference-dependent consumption utility and reduce the transportation cost of returning products, achieving a more efficient allocation of resources.

Keywords: Online reviews, purchasing decision, returning decision

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1. Introduction

With an accelerating rate of technological development and a general improvement in living standards, an increasing number of people discovered the convenience, diversity, and selectivity of online shopping. The outbreak of the global pandemic and the lockdown policy further induced the need for online shopping services. The increasing number of e-commerce sales worldwide (Fig. 1) stresses the significant role played by online markets.

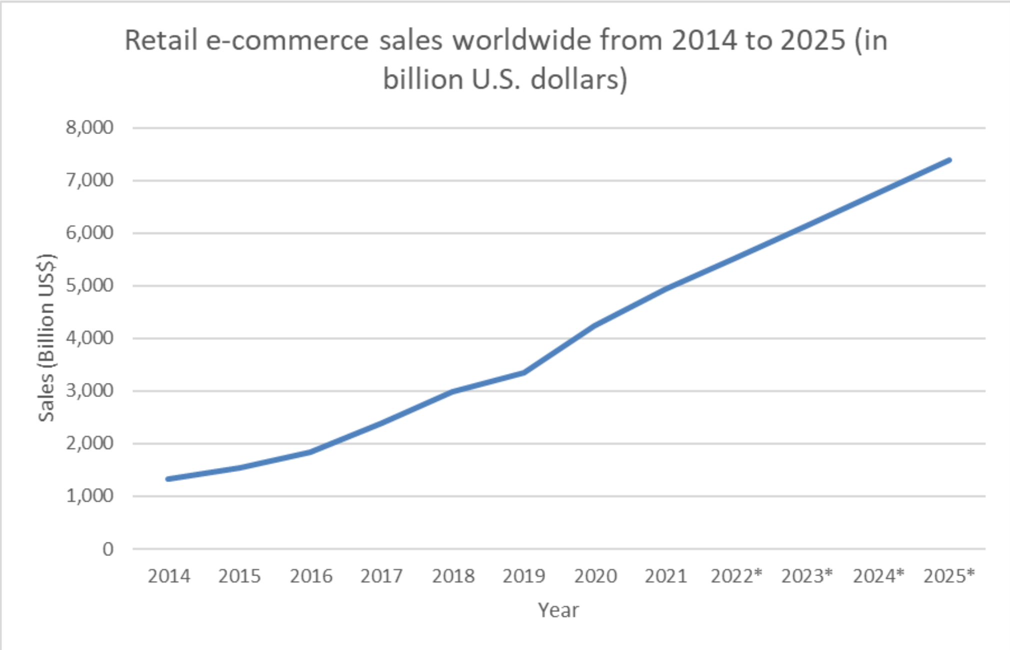

Figure 1: Retail e-commerce sales worldwide from 2014 to 2025 (*Source: Statista*)

Similar to other markets, individuals that are involved in the online market need to behave strategically. According to the theory of information transmission, asymmetric information is the obstacle for a competitive market to achieve efficient information exchange (Hayek, 1945).

When there exist conflicts of interest, people would be motivated to lie about messages the other party cannot access for higher profits. This could be demonstrated by the interaction between buyers and sellers. For instance, firms could choose the level of quality information to disclose when it comes to products that consumers cannot precisely evaluate actual quality. Zhao et. al. (2020) found that firms tend to disclose high-quality products and conceal low-quality products when facing strategic consumers. Inefficient allocation of resources is further exaggerated since online buyers cannot scrutinise the quality of online products.

However, when the interests of the two parties are aligned, the problem of asymmetric information can be alleviated. With low costs, informal talk and self-signalling constitute a major part of information sharing (Farrell and Rabin, 1996; Spence, 1974; Hurwicz, 1973). For example, since there is no conflict between buyers and former buyers, cheap talk via product ratings and reviews could improve the accuracy of information transmission. The existence of the third party restricts the seller's power of manipulating information about product quality to alter consumers' purchasing decisions. However, sellers also acknowledge the importance of comments from the third party. Therefore, they may pay people to write positive reviews and give higher ratings of the product. Moreover, many online shopping firms have shifted from online shopping to mobile shopping on apps. Some of the product information is concealed due to the reduced screen size, enabling sellers to adjust the layouts and guide consumers to buy their products.

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Overall, it would be important to investigate the behaviour of online buyers in response to various information that is true or fake, to achieve a more efficient allocation of resources.

Most of the studies investigated the effect of product reviews on sales, such as valence (Li & Hitt, 2008), volume (Chintagunta et al, 2010), and pathos of the reviews (Ren & Nickerson, 2016). Others are trying to find how individual-specific characteristics presented in reviews affect sales (Yin, 2020; Forman et al, 2008). However, only a few papers discuss the actual consumption utility after purchasing, namely, how reviews affect return rates. To fill the research gap, this paper investigates how revealed information such as online reviews, ratings, and selling amounts affect consumers' ex-ante quality beliefs and ex-post satisfaction to check whether consumers' quality beliefs based on reviews are biased.

This paper analyses information presented on e-commerce websites such as reviews, ratings, returns, and product types. However, due to the limitations of data collection, the analysis does not include information related to individual customers such as age, gender, wealth, or literacy level.

I analysed ex-ante consumer expectation and ex-post consumption satisfaction with cross-sectional data. To check how positive and negative review rates are associated with sales and returns, I ran 2-stage least square regressions with fixed effect of product types. The regression results show that the positive review rate is positively associated with sales and the negative review rate is negatively associated with sales. Similarly, the positive review rate is positively associated with returns and the negative review rate is negatively associated with returns. The outcome suggests that consumers form upward biased quality beliefs based on positive reviews, while the accuracy of negative reviews is relatively higher. Therefore, negative reviews could be more helpful when making purchasing decisions while positive reviews may give biased beliefs. To avoid overestimating actual quality, consumers could discount their expectations after forming quality beliefs. This would not only improve the reference-dependent consumption utility but also reduce the transportation cost of returning products. Thus, achieving an increase in both consumption utility and total welfare.

The paper proceeds as follows: Section 2 is a review of related literature. Section 3 outlines the theoretical framework in two parts. Firstly, describing the model of reference-dependent utility about how consumers form quality beliefs and how consumption utility is affected by consumer expectations and resulting propositions that I would like to prove in this paper. Secondly, giving a conceptual framework for constructing the dependent, independent, and control variables for the regression analysis. Section 4 is the summary of the data collected. Section 5 describes the modelling and results. Section 6 discusses the results and elaborates on causal relationships with behavioural factors. The conclusion in section 7 presents key findings and implications of the result.

2. Literature Review

We will initially approach this topic by looking at how consumers form quality beliefs.

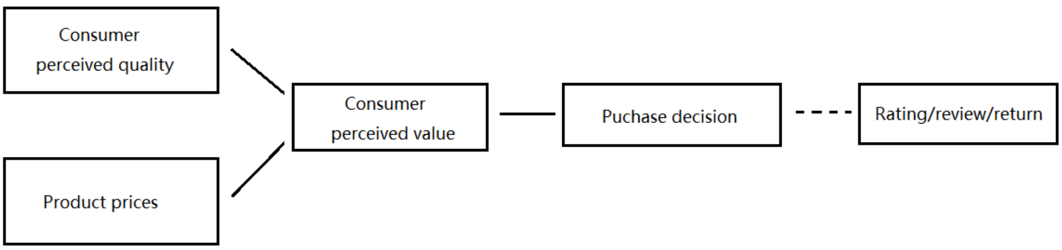

Figure 2: Customer valuation theory

According to the customer valuation theory (Fig. 2) (Zeithaml et al., 1996), consumers' perceived value is formed based on consumers' perceived quality and product prices. Since the perceived quality cannot be measured, consumers' purchasing decisions could act as a signal about consumers' perceived value. If consumers believe the

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product is worth buying given the prices, they would buy the product.

Price is the most important source of signals that are sent by sellers to reflect product quality. One of the areas of study is the price searching behaviour of online consumers with the impact of search costs, discounts, or attention. Moreover, other studies investigated consumers' valuation of the products (Jung et al., 2014), the effect of prices on shopping intentions (Wu et al., 2013), price sensitivity (Garrow et al., 2008), and price changes on consumer behaviour (Chatterjee, 2011; Weisstein et al., 2013). Moreover, due to differences in price elasticities of demand, price changes may result in different responses in sales. Furthermore, consumers tend to consider prices with other related factors. For expensive products, consumers prefer to buy from sellers with a large number of mixed reviews (positive, negative, and neutral) instead of buying from sellers with a small number but homogeneous positive reviews. While for low-priced products, consumers may be indifferent between the number of reviews and the configuration of reviews (Chou et al., 2013). Considering price as a source of losses, a lower price is associated with lower risks; while a high price means higher risks, thus a large number of former buyers may share the risk taken by the individual. Risk aversion is closely related to loss aversion when making buying decisions. Frey et al. (2017) proposed that revealed preference is one of the most used measurements of risk aversion. However, the empirical evidence is mixed. Moreover, there arises some criticism and scepticism about those measurements (Friedman et al., 2014; Beshears et al., 2008). Due to the validity of measurement results and the continuous changing of the propensity of each individual, real-world financial institutions seldom incorporate revealed preferences for analysis (Friedman et al., 2014). In this paper, I would like to assume all customers are risk-neutral and are indifferent between high-risk and low-risk products.

Consumer perceived quality is relevant to additional information such as ratings and reviews. Consumers' preferences may change according to different information received.

Many people post their ratings toward certain online products after consumption (Godes and Silva, 2012). Some e-commerce platforms exhibit histograms or pie charts to demonstrate the distribution of ratings; others may give an average rating of the product. Consumers could easily get cues regarding product quality from those statistics. Researchers explored the relationship between rating statistics and consumers' purchasing decisions (Chatterjee, 2001), and the result demonstrates a strong relationship between ratings and purchasing amount. Marketers, same as buyers, also acknowledge how influential the ratings and reputations are, paying someone to give high ratings in order to raise average ratings to attract more customers (Ludwig et al. 2013). Therefore, online reviews that affect consumers' perception would be needed to give more reliable information about actual product quality. Other than a simple number, online reviews that involve pictures, comments, and pathos are relatively more persuasive. Moreover, an online review forum could act as a trust-building device for online shopping since most of the members are former buyers. Kee (2008) suggested that about 70% of consumers read at least 4 product reviews before making a purchasing decision. The reliability of reviews, however, would depend on the incentive for former buyers to give comments about those products. The motivation of reciprocity or retribution that is purely due to consumption could give more reliable comments. Conversely, if former buyers receive a request with gifts from sellers to give positive reviews, the reliability may be impaired.

This paper, therefore, focuses on the relationship between online reviews and consumers' quality beliefs. Literature mainly falls into two categories: investigation of product reviews and the investigation of product returns. Starting from 2006, most of the studies devoted attention to the study of online product reviews and sales, while only a small number of studies explore the number of returns that may reflect consumer satisfaction.

Research generally corroborates the proposition that online reviews could influence consumers' buying decisions, therefore affecting the number of sales (Shen et al., 2016). For example, Clemons et al. (2006) and Duan et al. (2008) checked how ratings and reviews affect sales. Both of the studies found that positive reviews and the volume of reviews significantly improve sales on e-commerce platforms. A large part of the studies analysed different characteristics of reviews such as text length (Chevalier and Mayzlin, 2006), textual content (Archak et al, 2011), top reviews / expert reviews / peer reviews, recentness, and helpfulness (Huang et al, 2017; Jia and Liu, 2018). Findings corroborate the idea that consumers read review text in addition to summary statistics and ratings, therefore, textual content would affect sales as well as consumer preferences. Archak et al. (2011) used text mining to decompose reviews into segments describing different product features. Positive reviews and highly useful reviews have more adoption rates and improve consumers' attitudes towards the product and intentions to purchase the product.

Other studies look more deeply into the impact of consumers' characteristics and attitudes. For example, Forman et al. (2008) investigate how individual characteristics affect purchasing decisions, the result shows that identity-relevant information shapes community members' judgement of products and reviews. Therefore, consumers may address reviews or products that they are familiar with. Moreover, Branco et al. (2012) found that customers may incur search costs to learn further product information and update their expected utility of the product from time to time. The study incorporates search costs into investigating the likelihood of purchase changes with the ex-ante utility. Ren & Nickerson (2018) investigate the arousal level of reviews. Due to variances in arousal level, some studies may find online review valence is more influential, while others may find that online review volume could have more impact on sales. Similarly, Yin et al. (2020) studies anger expression. The study contradicts the view that more helpful online reviews exert a greater impact on consumer attitudes and purchase decisions. Their findings suggest that anger expressions may decrease customers' perception of the helpfulness of the review, the actual purchasing decision shows that anger expressions eventually are more persuasive and negatively influence customers' expectations toward products. However, Li et al. (2019) ran the regression with an interaction term of ratings and texts, finding that numerical ratings may mediate the effects of textual sentiments.

Meanwhile, some studies investigated product returns. Rather than trust online reviews, some consumers trust sellers' return policies more when making purchasing decisions. Firstly, we need to understand the formation of return rates. Hess and Mayhew (1997) show that return rates vary across product categories with some having return rates as high as 25% (e.g., shoes) and others having virtually no returns (e.g. socks). Moreover, the return rate becomes higher in online shops due to the convenience of returning products. Sahoo et al. (2018) managed to investigate the relationship between product reviews and product returns for offline shops and online shops. The result shows that unbiased online reviews help consumers make better purchase decisions, leading to lower product returns, while biased reviews that are recommended by sellers positively affect return rates.

With the development of e-commerce platforms, sellers pay more attention to modifying their review forums and concealing most of the return rates. Despite the research interest in online reviews and product returns, studies are generally unaware of the investigation into how online reviews affect both expectation formation (purchasing decision) and actual consumption utility (returning decision) for online products. This is a significant gap in the literature. Online reviews are significant sources of information when making purchasing decisions, meanwhile, the return rate is a vital indicator of consumption utility. By investigating the impact of online reviews on sales and corresponding returns, this paper fills this gap.

3. Theoretical Framework

3.1. A Model of Reference-Dependent Utility

Since people's perceptions, judgments, and evaluations are relativistic and adaptable, consumers are generally characterised by reference-dependent utility (Kahneman & Tversky, 1979). In the context of this paper, the reference point (r) or ex-ante expectation is the combination of consumers' perceived quality and prices according to the customer valuation theory.

$$r = E(c) = f(perceived\ quality, price)$$

Consumers would buy the product if and only if the ex-ante expectation is greater than 0. The expected utility would be affected by both the impact imposed by product reviews and consumers' propensity (Elster, 1989).

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From the consumers' perspective, an important behavioural factor, limited attention, may alter consumer's perceived value of the product. Assume that an individual pays full attention to the visible component of the value but only partial attention to the opaque component (i.e. ratings). Suppose a consumer perceives the value

$$\hat{V} = v + \theta o$$

θ measures the degree of inattention: the higher θ is, the more attentive the consumer is to the opaque component. Therefore, the perceived quality in the model would then be:

$$Perceived\ Quality = v + \theta o$$

The value of the reference point would change correspondingly. I will elaborate on the effect of inattention in the discussion.

To further understand consumers' perceived quality, I will examine how online reviews, the primary source of information, are formed. In particular, what the underlying incentives for consumers to give insights from their consumption experience are. Although online reviews always appear in large numbers, research shows that not all consumers tend to provide reviews of products, thus resulting in biases in the evaluation of the quality of the product. Both intrinsic and extrinsic motivation could trigger the consumer to write reviews. Intrinsic motivation means that people are doing activities simply for the enjoyment of the activity itself, while extrinsic motivation is defined as doing something for a separable outcome (Ryan & Deci, 2000). Given these motivations, reference dependent utility would be one of the explanations for the appearance of positive and negative reviews.

Prospect Theory (Kahneman & Tversky, 1979) requires people to consider reference points in addition to consumption while Kőszegi and Rabin (2006, 2007, 2009) re-introduced the standard consumption utility and assume utility is separable from reference-dependent utilities. By separating consumption utility and reference-dependent gain-loss utility, we can analyse consumer behaviour more precisely. Therefore, this paper modifies the model proposed by Kőszegi and Rabin to explain consumer behaviour in online buying. Individuals' reference-dependent utility is given by:

$$u(r) = m(c) + n(c|r)$$

Where *m(c)* represents the consumption utility of the products and *n(c|r)* represents the gain-loss utility. Consumption utility *m(c)* is assumed to be increasing and globally concave like standard expected utility, thus exhibiting decreasing marginal utility. The gain-loss utility is calculated as a function of the difference between consumption utility and the reference point, consumers' expected consumption utility:

$$n(c|r) = \mu[m(c) - E(c)]$$

The function *μ* is the gain-loss function. According to loss aversion (Kahneman & Tversky, 1984), losing something generally weighs heavier than gaining the same thing one does not own. The same situation could be applied to online shopping where people have the perception of owning something before physically receiving it. When the perceived gains are higher than actual gains, people may feel more disappointed than additional satisfaction when there are higher actual gains. Therefore, I would propose the gain-loss utility as:

$$n(c|r) = \mu(x) = \begin{cases} \eta x & if\ x > x^* \\ \lambda\eta x & if\ x < -x^* \\ 0 & if - x^* \leq x \leq x^* \end{cases}$$

x* represents the value of a threshold of the difference between actual utility and expected utility. When the difference is higher than the threshold x*, there would be a gain, the utility would be calculated by multiplying a coefficient η; When the difference is lower than the threshold -x*, there would be a loss, the utility would be calculated by

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multiplying two coefficients λ and η; when the difference is between the two thresholds, the gain-loss utility would be zero.

There are 3 possible intrinsic motives in the model, resulting in 4 possible results: writing positive reviews, negative reviews or neutral reviews, and returning products. When consumers think the actual utility gained from consumption is much higher than perceived utility ($x>x^*$), people tend to give positive reviews or even positive reviews with pictures to praise the good quality of the products. This may be due to the incentive of reciprocity (Fehr & Gachter, 2000). In response to friendly actions, people tend to be nicer and more cooperative. Namely, since the product received exceeds consumers' expectations, people may attribute this difference to the seller, therefore are willing to help the seller by recommending the products to others. Conversely, when consumers think the actual utility gained from consumption is much lower than the perceived utility ($x<x^*$), people tend to give negative reviews or even negative reviews with pictures to stress the poor quality of the products. This may be due to the incentive of retribution (Boehm, 1984). The negative feelings of consumption would be reflected in negative reviews so that notify others to keep away from those products. Other than posting negative reviews, consumers could choose to return the product without giving any comments. This response relates to consumer satisfaction but is seldom taken into account in studies. Therefore, this paper includes this behaviour in empirical analysis. Lastly, consumers may be indifferent between posting positive or negative comments about the products when the quality is similar to their expectation ($-x^* \leq x \leq x^*$), therefore, they may not provide their experience. Above all, peer reciprocity could act as a main motive to provide reviews. For example, 32% of the participants in Munzel & Kunz's (2014) study indicate that they prefer giving reviews to benefit the community.

Literature proposes other behavioural factors that may affect consumers' decisions to provide product reviews. Altruism is the main factor that gives intention to consumers to write reviews (Reimer & Benkenstein, 2016). Studies show that altruism is a fundamental motive for consumers to provide product reviews and an altruistic individual may give slightly more useful reviews compared to others (Munzel & Kunz, 2014; Cheung & Lee, 2012). However, the role of altruism is still unclear when it comes to analysing the number of reviews. Therefore, this paper will not take altruism into account in the empirical analysis.

Sellers tend to provide extrinsic motives to further increase positive reviews. Although extrinsic motivations tend to crowd out intrinsic motivations (Deci et al. 1999), weak extrinsic motives such as a request from the seller to write reviews could give more positive feedbacks. For example, Munzel and Kunz (2014) found that when hotels ask visitors to provide reviews, there are an increasing number of reviews. Further, a request with a small gift could achieve a better result as Wu (2019) corroborates the reciprocal behaviour of consumers. Financial incentives are a relatively stronger motive for customers to provide reviews (Straaten, 2021). Although it is unclear how financial incentives affect the valence of reviews, Neumann & Gutt (2019) found that monetary motives could increase the volume of reviews. Adding monetary incentives (i.e., voucher) in the theoretical model gives:

$$u(r) = m(c) + n(r) + u(voucher)$$

In this way, the increase in total utility u(r) by u(voucher) would give higher possibility for consumers to write positive or neutral reviews.

Due to the loss-aversion motive in the reference-dependent utility and the underlying incentives of providing product reviews, I put forward:

Proposition 1: Negative reviews are generally less in number compared to positive reviews, but customers may rely more on negative reviews when making a purchasing decision.

- If consumers give more trust to negative reviews, higher negative review rates would give lower sales

Moreover, consumers need to engage in strategic thinking and have limited cognitive ability to precisely evaluate the quality of products. To elaborate, consumers may not be able to capture and process all information provided by the seller and the third parties. Customers may easily be attracted by particular identities, words, or emotions

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expressed in texts. Therefore, consumers tend to employ heuristics (i.e., specific positive reviews) to simplify the decision-making process to prevent cognitive overload. This would lead to systematic biases in the valuation process. Thus, I put forward:

Proposition 2: Consumers' expectations about the quality of the products are biased.

- If consumers form higher-quality beliefs from a positive review, positive reviews would associate with higher return rates.
- If negative reviews carry more accurate quality information, negative reviews would associate with lower return rates.

3.2. Conceptual Framework

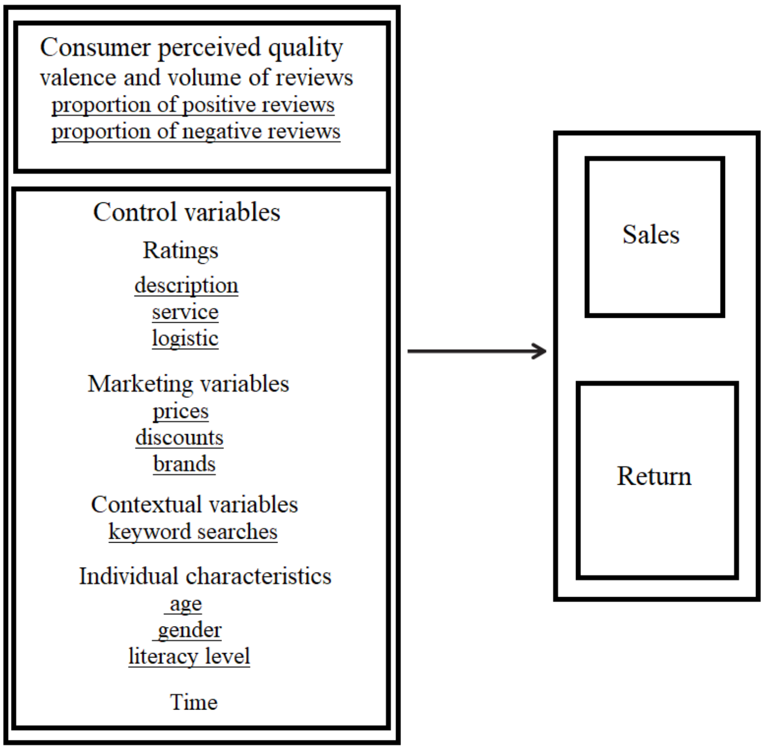

Figure 3: Conceptual framework on how reviews, ratings, product, and individual characteristics affect sales and returns

3.2.1. Dependent Variable

In accordance with the analytical model above, I propose that there are two decisions that the consumer needs to make: purchasing decision and returning decision. Purchasing decisions could be represented by the number of sales on the seller's website. However, the sale amount does not subtract the number of returns. Therefore, the actual satisfaction could be indicated by the return rates. Since sellers tend to conceal actual return rates even if the platform asks for disclosure, the return rates are generally 0% and may not be representative. There are other return statistics as well, such as the time span for returning request acceptance and the time span for receiving refunds. Moreover, sellers' willingness to return (WTR) is also included in return statistics. WTR is calculated by:

$$\frac{No.of\ returns\ resolved\ by\ sellers}{No.of\ returns\ resolved\ by\ sellers\ +\ No.of\ returns\ resolved\ by\ the\ platform}$$

In Taobao, the seller and the platform are two entities, the seller has the power to decide whether to accept the return request from customers. If the customer is unsatisfied with the sellers' decision on the return request and the

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customer's appeal is reasonable, the customer could seek help from the platform. The platform has the power to make the seller accept the return request. According to Zhao et al. (2020), sellers conceal product quality when the true quality of the product is poorer than the actual quality, thus tend to be more unwilling to accept return requests; the willingness to return (WTR), in this way, could reflect the actual quality of products. Therefore, returns would be calculated by the average of return rates, return span, refund span, and 1-WTR. There would be two regressions for ex-ante perception and ex-post satisfaction, with sales and returns as dependent variables respectively.

3.2.2. Independent Variables

Consumers need to form a quality expectation about the product. The review forum could give specific information about the product. The number of positive reviews and negative reviews could help consumers know the proportion of customers that are satisfied with the product. When considering the number of positive and negative reviews, the data may result in the problem of reverse causality. Namely, the number of positive reviews affects sales, but the number of sales affects the number of positive reviews as well. In order to minimise the effect of reverse causality, I calculated the proportion of positive and negative reviews among all reviews as the independent variable – positive review rates and negative review rates.

$$positive/negative\ review\ rates = \frac{number\ of\ positive/negative\ \ reviews}{total\ number\ of\ reviews}$$

Since sales could affect both the number of positive (negative) reviews and the total number of reviews, the effects could offset each other as it is presented in both numerator and denominator. Moreover, despite positive and negative reviews, some customers are unwilling to spend time writing reviews or are indifferent between positive or negative reviews as I mentioned earlier, they tend to post a neutral review. Since the neutral review rate is calculated as 100% less the percentage of positive and negative reviews, this variable may result in the problem of collinearity. Therefore, we only use positive review rate and negative review rate as independent variables for regression. In addition, Sahoo et al. (2018) mentioned fit information in the study. Fit information is whether the product fits specific individuals, for example, the size of clothes. Therefore, the helpfulness of certain reviews would be different for different individuals. Controls for these are discussed below.

3.2.3. Control Variables

Control variables include marketing variables, contextual variables, and individual characteristics. For marketing variables, prices, ratings, discounts, and brands could all result in changes in consumer decisions. Prices include the prices of the product and the price of transportation. Some of the retailers charge high transportation costs (return costs) in order to prevent returning products. Therefore, I choose sellers with low or without return costs. Numeric ratings could help consumers get a general idea about product quality. Both average ratings of a specific product and whether the average ratings are higher or lower than ratings of other close substitutes are important. Discounting is a popular marketing strategy to attract consumers and improve positive review rates. Therefore, the degree of discount needs to be controlled. Moreover, brand loyalty means some consumers trust only a few brands and buy products from those brands. So that reviews and ratings may not change their purchasing decisions. Therefore, I eliminate the effect of brands by dropping data collected about specific famous brands such as Nike. People may hold different preferences towards various categories of products. Therefore, I choose 5 categories of products with the highest sales among all categories: Food, stationeries, clothes, shoes, and electronics. I tried different keywords to find close substitutes from these categories to omit potential biases due to differences in product categories. Therefore, I included sub-categories under the general 5 categories according to different keyword searches.

Customers' characteristics could also affect their purchasing decisions. For instance, they may choose to buy products that seem familiar and trust reviews written by a person who carries similar characteristics. However, due to the protection of consumer privacy, the data I collected from the e-commerce platform does not include information related to customers.

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Time is another variable that may change consumer purchasing decisions, especially in the context of the global pandemic. For example, at the beginning stage of the pandemic outbreak and lockdown, the sales of facial masks would increase and reach a scarce level, therefore, consumers may not care about ratings and reviews. Afterward, people may address the storage of foods. In these periods, the fluctuations in sales amount may not be representative. Therefore, product statistics are collected from the e-commerce platform in March 2022.

Above all, the hypothesised effects of positive review rates and negative review rates on sales and returns are presented in Table 1 according to propositions and the theoretical model. Positive reviews would have a positive effect on sales while negative reviews would have negative effects on sales. However, since the reviews could be biased, consumers tend to overestimate the actual product quality given positive reviews, therefore, a higher proportion of positive reviews could lead to a lower level of satisfaction and a higher rate of returns.

Variables	Hypothesised effect on sales	Hypothesised effect on returns
Positive review (%)	+	+
Negative review rates (%)	-	-

Table 1: Hypothesised effect of independent variables on sales and returns

4. Data

Data are collected from the largest e-commerce retailer in China, Taobao. Due to the prevalence of big data technology, the keyword searching result is personalised, showing different prices or quality of products to different individuals according to their previous buying patterns. Therefore, I collected the data using 3 users' login details. Python codes for collection are in Appendix 2. The information for products is collected in March 2022. All the data collected are exactly the same information that other consumers could access, thus, the result could mimic how consumers process the information and reach the final purchasing decision. The return statistics, which consumers with mobile apps cannot access, are used to measure ex-post satisfaction levels.

The data set includes 1749 randomly selected products. It consists of information about products, product reviews, ratings, purchases, keywords (categories), and returns. The description of the dataset is found in Table 2.

Variable	Observations	Mean	Std. dev.	Min	Max
Price	1,749	517.62	1000.57	1.8	5498.00
Sales	1,749	7627.89	12449.96	1	200000
			Reviews		
Positive %	1,749	26.71	24.33	0	100
Negative %	1,749	27.70	72.72	0	100
Neutral %	1749	45.70	71.26	0	96.20
			Ratings		
Description	1,749	4.80	0.07	4.5	4.9
Service	1,749	4.76	0.07	4.5	4.9
Logistic	1,749	4.81	0.07	4.6	4.9
Return	1,749	4.65	0.38	2.79	5.04

Table 2: Summary of the data

Sale amounts could reflect consumers' purchasing decisions. Return is calculated by the average of return rates, return span, refund span, and 1-WTR. These are the two dependent variables for two regressions. According to the

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customer valuation theory, prices are also an important factor that affects consumers' decision-making process. The valence and volume of positive and negative reviews are included in the form of the proportion of positive / negative reviews among all reviews. Ratings about the product are divided into three categories: description, service, and logistics. The "description" is about whether the product description is in accord with actual quality; "service" includes consumers' evaluation of sellers' attitudes; and "logistics" is about the speed and quality of transportation of the products. The description of variables is illustrated in Table 3.

Variable	Description
Sales	The dependent variable: the number of sales of the product within March 2022
Returns	The dependent variable: average of return rates, return span, refund span, and (1-WTR) within 30 days
Price	The price of the product at the time of purchasing
Positive %	The proportion of positive reviews at the time of purchasing
Negative %	The proportion of negative reviews at the time of purchasing
Ratings (1-5)	The average ratings of the products, including ratings about product description, services, and logistics

Table 3: Description of variable names

Before describing the econometric model, I would like to show the plots that visually depict how sales and returns vary with different categories of products. The box graphs (Fig. 4) demonstrate the impact of different categories on sales and product return rates.

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a)

b)

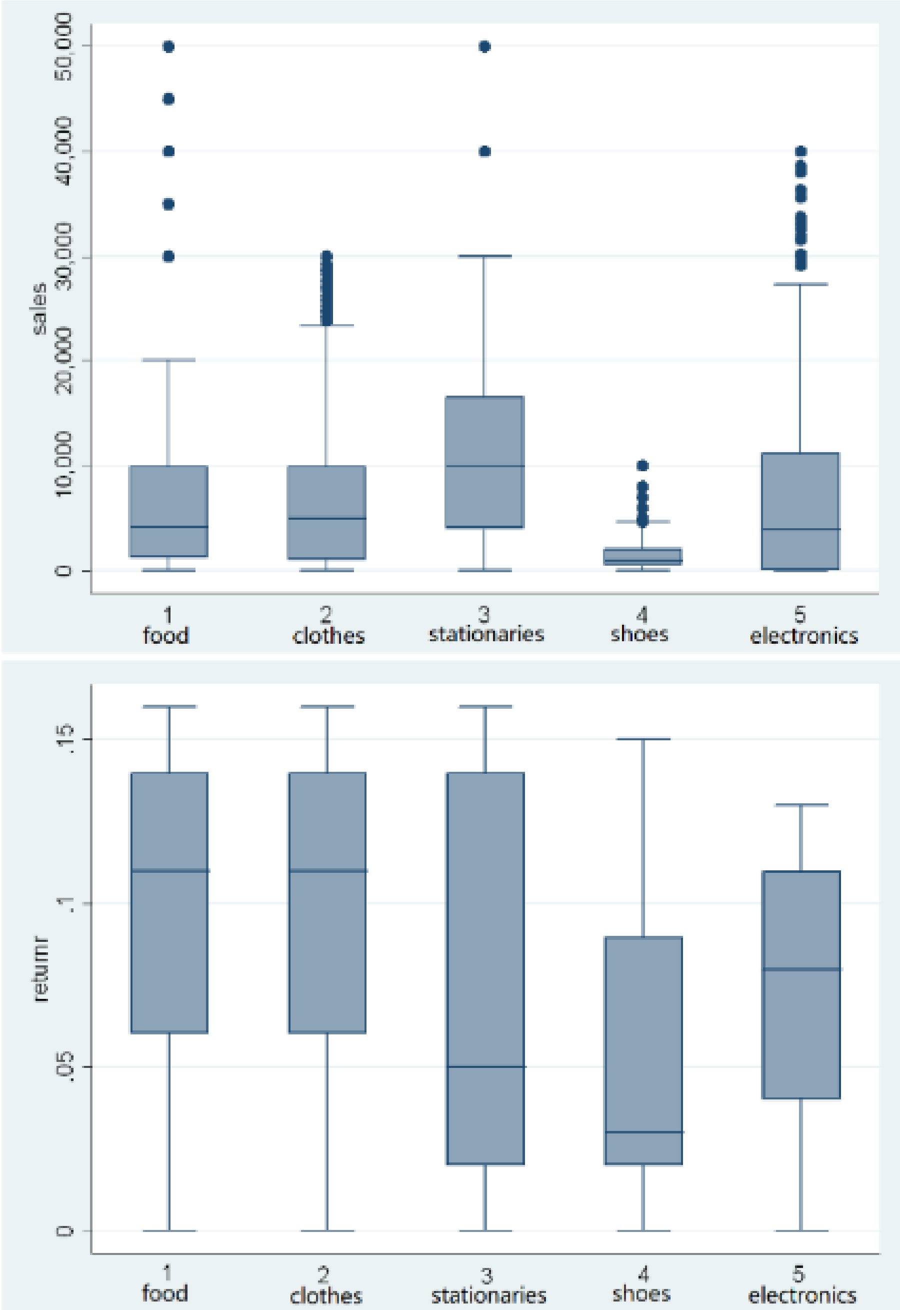

Figure 4: Box plots of a) sale and b) return rates by product category

We see that the sales for stationaries are the highest and the sales for shoes are the lowest. Moreover, the range of sales for food and electronics is large so these two categories have more extreme values. The average return rate for stationery and shoes is relatively low, while for food and clothes is generally high. The two scatter graphs (Fig. 5) plot the number of sales against the positive and negative review rates.

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a)

b)

Figure 5: No. of sales vs a) positive review rate and b) negative review rate

Similarly, two graphs below (Fig. 6) plot the return statistics against positive and negative review rates.

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a)

b)

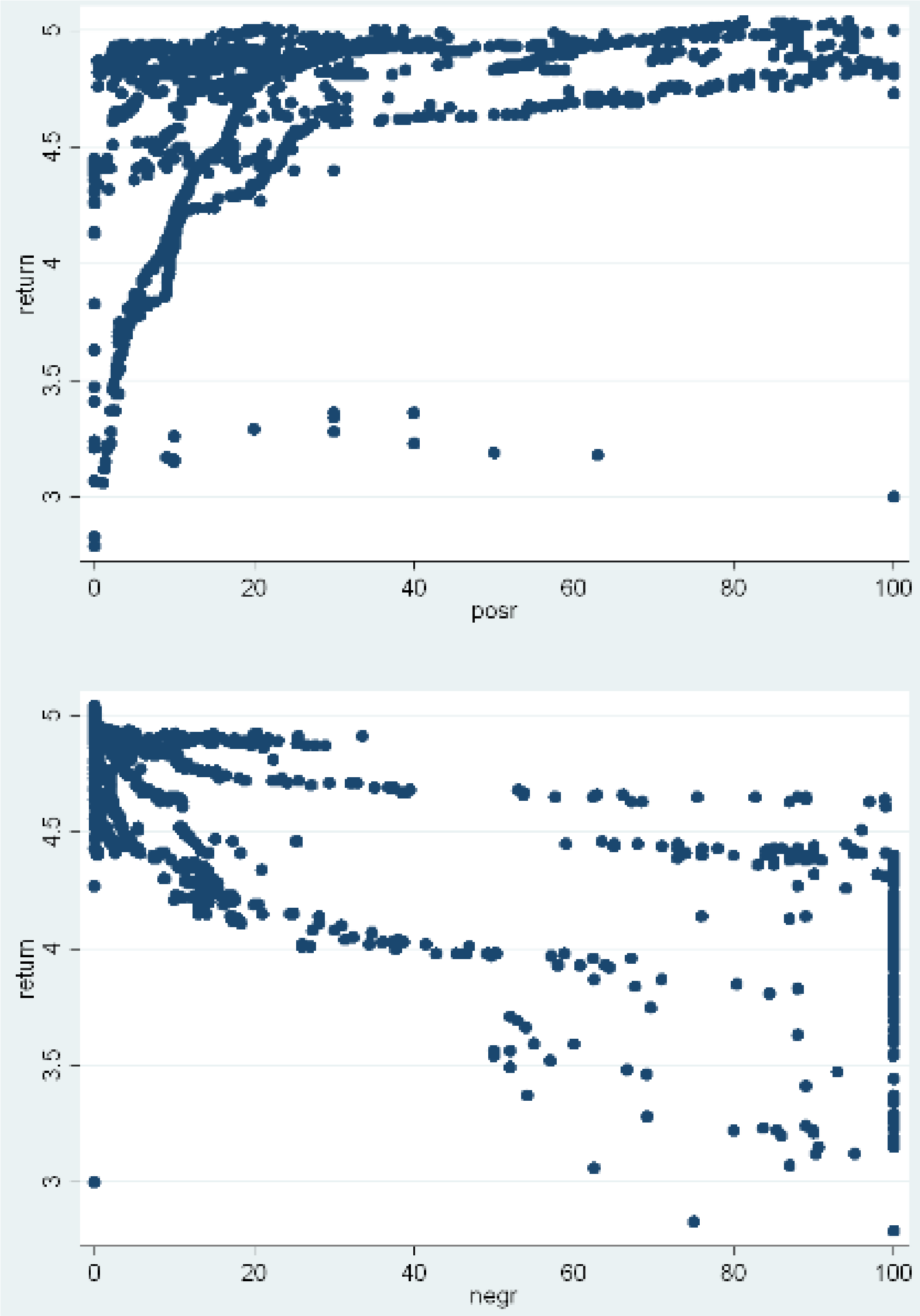

Figure 6: No. of returns vs a) positive review rate and b) negative review rate

To get a precise estimate of the effect variables of interest, a more complete model that controls other factors is needed.

5. Modelling and Results

Previous studies mainly used two models to estimate the effect of product reviews: the OLS-fixed effect model with Granger causality tests and binary choice model with maximum likelihood estimation. Given the nature of the data I

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collected, this paper uses least squares estimation.

There are two main assumptions for this model. Firstly, all consumers are risk-neutral so that they are indifferent between high and low risks in the trade-off between price and quality. Secondly, product descriptions are similar among close substitutes which means that consumers could only use information from third parties to distinguish among those products.

5.1. Ex-ante Expectations

For ex-ante expectations, consumers generate the perceived value of the products from the price of the product (P) and the perceived quality (Q). The perceived quality is the function of ratings, positive review rates, and negative review rates. Therefore, the regression model is:

$$ln\ Sales_i = \alpha + \beta^{'} Q_i + \gamma P_i + \varepsilon$$
$$Q = g(ratings, positive\ \%, negative\ \%)$$

However, this regression would have the problem of endogeneity. Therefore, I control for product categories in the regression:

$$ln\ Sales_{ijk} = \alpha_{jk} + \sum_j \sum_k \beta^{'} z_{ijk} + u_i$$

α_{jk} is the category-specific fixed intercept to control for category-specific unobserved characteristics that affect sales. j represents the general categories of products. k represents the sub-categories in general categories, for example, staple food or snacks in the food category. z_{ijk} represents the explanatory variables, with the coefficient matrix $\beta^{'}$.

j	Food		Clothes		Stationery		Shoes		Electronics	
k	Staple	Snacks	Shirts	Trousers	Pens	Notebook	Formal	Casual	Large (i.e.laptop)	Small (i.e. headphones)

Table 4: Category Controls

To further reduce the endogeneity problem, I use an instrument variable for the endogenous variables of positive review rates. Apart from intrinsic motives for writing reviews, extrinsic motives such as monetary incentives could also affect positive review rates. Therefore, I collected data about whether the seller gives monetary incentives to the customer and asks for positive reviews. Since the monetary incentive (MI) is provided after making the purchase, this variable provides an exogenous variation in the dependent variable of interest without causally affecting the outcome of interest. MI affects positive review rates and give high ratings, indirectly affecting the dependent variable. Hence, the two assumptions for an instrument variable, exclusion ($Cov(MI_i, \varepsilon_i) = 0$) and relevance ($Cov(MI_i, Q_i) \neq 0$), hold. Therefore, we have the first stage regression:

$$pos\%_{ijk} = \theta_{jk} + \sum_j \sum_k \delta\ MI_{ijk} + v_i$$

The regression results are presented in Table 5, where (1) has no category-specific fixed effects, (2) has category controls, and (3) is the 2SLS regression with category controls.

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Independent Variable	(1)	(2)	(3)
Positive %	0.0012* (0.0001)	0.0101*** (0.0009)	0.0384** (0.0026)
Negative %	-0.0411* (0.0025)	-0.0482*** (0.0007)	-0.0486*** (0.0010)
Price	0.0001 (0.0001)	-0.0001*** (0.0000)	0.0001 (0.0002)
Description	4.6754** (0.8662)	2.7718** (0.2736)	1.7398 (1.0952)
Service	5.2472** (0.9754)	2.6876** (0.3084)	0.3603 (2.2128)
Logistic	3.2075 (0.8481)	2.5475* (0.2716)	0.5488 (1.9375)
Food *(staple)*	-	0.0305*** (0.0652)	0.0291*** (0.0814)
Clothes *(trousers)*	-	0.0207 (0.0651)	0.0315 (0.0787)
Stationery *(pens)*	-	0.0068** (0.0650)	-0.0037 (0.0786)
Shoes *(formal)*	-	-1.0461*** (0.0699)	-0.0429 (0.0801)
Electronics *(small)*	-	0.0270 (0.0844)	0.1046 (0.1210)

Table 5: Regression results with *ln(sales)* as dependent variable (standard errors in brackets)
* significant at 10%, ** significant at 5%, *** significant at 1%

5.2. Ex-post Consumption Utility

For ex-post consumption, the return rates could be a good measure of consumer satisfaction besides than reviews. Similar to the above regression model:

$$return = \alpha + \beta' Q + \gamma P + \varepsilon$$
$$Q = g(ratings, positive\ \%, negative\ \%)$$

In order to solve the problem of endogeneity, I add the product fixed effect,

$$return_{ijk} = \alpha_{jk} + \sum_j \sum_k \beta' z_{ijk} + u_i$$

α_{jk} is the category-specific fixed intercept to control for category-specific unobserved characteristics that affect returns. j, k, and z_{ijk} represents the same things as before. Further, I use the same instrument variable MI for the endogenous variable positive review rates, with first stage regression:

$$pos\%_{ijk} = \theta_{jk} + \sum_j \sum_k \delta\, MI_{ijk} + v_i$$

The results of the regressions are presented in Table 6, where (1) has no category-specific fixed effects, (2) has category controls, and (3) is the 2SLS regression with category controls.

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Independent Variable	(1)	(2)	(3)
Positive %	-0.0013 (0.0003)	-0.0007** (0.0004)	0.0023* (0.0006)
Negative %	-0.0065** (0.0003)	-0.0064*** (0.0003)	-0.0061*** (0.0002)
Price	-0.00004** (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
Description	0.3361* (0.1183)	0.4318*** (0.105)	0.5276** (0.2511)
Service	0.8194* (0.1332)	0.7704*** (0.1182)	0.6349 (0.5074)
Logistic	0.4038 (0.1158)	0.3701** (0.1041)	0.2125 (0.4442)
Food (staple)	-	-0.0073 (0.0250)	0.0033** (0.0187)
Clothes (trousers)	-	-0.0054 (0.0250)	-0.0037* (0.0180)
Stationaries (pens)	-	0.0045 (0.0249)	0.0031 (0.0180)
Shoes (formal)	-	0.0302 (0.0250)	0.0287 (0.0184)
Electronics (small)	-	-0.0290 (0.0324)	-0.0073 (0.0277)

Table 6: Regression results with *Return Rate* as dependent variable (standard errors in brackets)
* significant at 10%, ** significant at 5%, *** significant at 1%

6. Discussion

6.1. Information from Reviews and Control Variables

For the ex-ante regression, the positive review rates at the time of purchase have a significant positive association with the change in sales. A 1 percentage point change in positive review rate is associated with a 3.8% change in sales. Moreover, negative review rates at the time of purchase have a significant negative association with changes in sales. A percentage point change in negative review rates is associated with a -4.8% change in sales. This supports proposition 1 that negative review rates may have a larger association with sales.

While for the ex-post regression, the coefficients for positive review rates and negative review rates show a similar trend. The positive review rates at the time of purchase have a significant positive association with change in returns. 1 percentage point change in positive review rate is associated with a 0.23% change in returns. Moreover, negative review rates at the time of purchase have a significant negative association with changes in returns. 1 percentage point change in negative review rates is associated with a -0.61% change in sales. This result could support the second proposition that consumers form upward biased expectations from positive reviews while negative reviews would give a negative association with returns. In order to further test the second proposition, we could show the coefficients for positive review rate in the two regressions have the same signs and the coefficients for negative review rate in the two regressions have the same signs via the student t-test.

With H_0: $\widehat{\beta}_{pos\%} = 0$ and H_1: $\widehat{\beta}_{pos\%.} > 0$; H_0: $\widehat{\beta}_{neg\%} = 0$ and $H_{1:}$ $\widehat{\beta}_{neg\%} < 0$ for both regressions. The formula for the t-value is:

$$t = \frac{\hat{\beta} - 0}{se(\hat{\beta})}$$

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The null hypothesis is rejected at a 5% significance level. Therefore, the coefficients for positive review rate in the two regressions are positive and the coefficients for negative review rate in the two regressions are negative. The result implies that consumers tend to form biased beliefs about quality products with positive reviews.

Ratings of the product have more space for the sellers to manipulate. For ex-ante expectation formation, we could see that ratings of the description of the product have a relatively higher association with sales (1.7398) compared to ratings about services and logistics. Moreover, rating for services has the least importance for the consumer to consider when making purchasing decisions (0.3603). On the contrary, for ex-post returning decisions, ratings generally have a significantly higher association with returns. Ratings about product description and logistics are associated with 0.5276 and 0.2125 increases in returns. While the rating of services has a larger association with returns, which is 0.6349. Overall, consumers pay more attention to product descriptions when making purchasing decisions, while the attitude of the seller and service quality becomes deterministic when consumers make returning decisions.

Prices are positively associated with sales. When taking prices in the form of cost, a higher price would result in lower sales; however, when price acts as an indicator of quality, a higher price may imply higher quality, therefore, a higher price would result in higher sales. The association between prices and returns is 0.00001 and not significant, implying that prices may not affect returns in general.

6.2. Explanations with Behavioural Factors

Due to bounded rationality, consumers' behaviour usually depends on mental shortcuts rather than elaborated processes that calculate the expected quality of products. Therefore, we need to consider behavioural factors that cannot be quantified but could act as mental shortcuts. In this way, we could infer the underlying explanations for the regression result. In this section, we mainly discuss behavioural factors that are related to individual characteristics, including status quo bias, inattention, social proof, liking and authority, and scarcity.

6.2.1. Status Quo Bias

Once people choose or write something, they tend to stick with their standpoint. People's tendency for commitment and consistency could raise the predictability of their behaviour. This would result in brand loyalty or consumers' commitment to certain sellers. For example, people tend to buy products from a single seller, therefore generating brand trust and brand loyalty. In this way, there would be a positive feedback cycle that raises both sales and the number of positive reviews of the seller. Besides, the mere agreement effect (Pandelare et al., 2010) states that people are much more likely to agree to a subsequent request if they have a positive response to requests beforehand. This could be interpreted as a consumer who purchases the product being more likely to follow the seller's request to write a positive review, therefore the number of positive reviews could be closely correlated with sales. Further, sellers tend to provide both intrinsic and extrinsic motivations to guide consumers to make a determined commitment. For instance, sellers could give discounts or coupons for later consumption, this strategy engages customers for their own benefits and results in uplifting sales for especially retailing products (Humby, 2004). External motivation involves positively labelling consumers as above average when consuming certain types of products (this could be represented by a higher price especially for luxuries), the psychological hint could result in higher involvement rates (Tybout & Yalch, 1980). However, the salience of labels would decrease over time so the increases in sale amount would be temporary. In addition, status quo bias implies that people tend to be reluctant to return products once they receive them. This could explain the smaller estimators (0.0023 < 0.0384) for regression of returns.

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6.2.2. Inattention

Independent Variable	(1)		Independent Variable	(2)	
Positive %	0.0430**	0.0144	*Positive %*	0.00361*	0.00442
Negative %	-0.0503***	0.0029	*Negative %*	-0.00723***	0.00090
Price	0.0001	0.0001	*Price*	0.00003	0.00003
Food (staple)	0.0283	0.0856	*Food (staple)*	-0.00950	0.02622
Clothes (trousers)	0.0243	0.0855	*Clothes (trousers)*	-0.00312	0.02619
Stationeries (pens)	-0.0041	0.0859	*Stationeries (pens)*	0.00319	0.02630
Shoes (formal)	-0.0254	0.0874	*Shoes (formal)*	0.03823	0.02677
Electronics (small)	0.0578	0.1439	*Electronics (small)*	-0.03483	0.04409

Table 7: Regression results with (1) *ln(Sales)* and (2) *Return Rate* as dependent variable
* significant at 10%, ** significant at 5%, *** significant at 1%

Individuals may not pay full attention to all the information presented by the seller. As I have mentioned earlier, ratings are often put in less visible corners of webpages. Therefore, buyers may ignore ratings when making purchasing decisions. As such, I run the 2SLS regression with fixed category effects but without the effect of ratings. The result is illustrated in Table 7. We could see that although we are not controlling the effect of ratings, the results for positive review rates and negative review rates are significant and support the propositions. Ratings, therefore, may not play a pivotal role in determining consumer perceived quality of the product.

6.2.3. Social Proof

Social proof is another influential factor that affects consumer behaviour. People naturally refer to others' actions as a cue on what to do when they are uncertain about something. This means that only when the person is hesitating between close substitutes, the influence of others' decisions could be successful. In the context of this paper, when people form a quality belief about a specific product, they tend to refer to others' consumption behaviours even when other people's purchasing decisions are wrong. Asch's experiment on social conformity verified the proposition that people tend to trust others' choices even if they are wrong. Nord and Peter (1980) also suggested that people may adjust their behaviour to follow others. When consumers are hesitating among close substitutes, the number of sales could be a direct clue for other consumers' behaviour. People tend to buy products with higher sales so the number of sales could affect the number of reviews and consumers' buying decisions. Moreover, the positive reviews could create an indirect clue for others' behaviour which is far more effective than direct messages. When consumers are uncertain about the expected quality, they tend to seek clues from product reviews, therefore, positive reviews could play a significant role in determining consumers' perceived quality - consequently giving biased quality beliefs.

6.2.4. Liking & Authority

People are susceptible to things with particular similarity, closeness, in-group feeling, attractiveness, and familiarity. Specific characteristics that are mentioned in reviews, similar identities disclosed by the reviewer, or particular in-text sentiments could all create a sense of liking between unfamiliar people. In this way, consumers tend to trust reviews from customers with similar characteristics (Forman et al, 2008). A recommendation from authority is influential as well. This includes authority-directed signals (i.e. brands, superstars) or legitimate authority positions (i.e. nutritionists, doctors, professors). This could be because those who are in authority positions have usually demonstrated certain skills to get to that particular position so trusting them could be beneficial via a heuristic mental

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shortcut to make good decisions or rational choices. However, the problem is, people do not need to be an expert to show authority; appropriate signalling is enough. Making two-sided arguments or powerful language when writing product descriptions or reviews could make the texts seem more persuasive. Studies (Yi et al., 2019; Sahoo et al., 2018; Huang et al., 2017) support the proposition that variances in the language of online reviews would alter consumers' decision-making. People tend to follow reviews with longer text lengths or persuasive tones, ignoring other information that may be useful. With recent studies in China, those who are employed by the seller to write positive reviews need to write “high quality” reviews to attract consumers. Therefore, consumers tend to trust those high-quality reviews and overestimate product quality.

6.2.5. Scarcity

Lastly, scarcity plays a deteriorating role in the robustness of the data at different times. When people believe something is scarce or difficult to obtain, in quantity, time, or availability, they tend to add value to that thing, resulting in an upward biased expected quality. Therefore, consumers are compelled to buy something they do not need or would not buy normally. Due to the global pandemic and the lockdown policy, people prefer storing a certain amount of food in case of emergency. Especially in January 2022, the Chinese government indicated that families need to ensure food storage. This policy resulted in a jump in the sales of staple foods in January, and there is a decreasing trend in sales afterward. In this way, people's purchasing decisions would be irrelevant to other information since they only care about the product itself. This situation could apply to medical products such as disinfectants or face masks that may change with the outbreak of the pandemic. Another way to interpret scarcity is about sellers' strategy, this applies to the sale of limited-edition shoes or electronic devices. Sellers usually use "last chance" or similar words to show supply-based scarcity. Whether this tactic could be successful is closely related to the sellers' reputation (Lee et al, 2014) or brands. In this way, the effect of scarcity would make sales a self-perpetuating factor and induce increases in buying orders.

Above all, behavioural factors could explain biased quality beliefs. Hence, customers could employ techniques that help them to make higher-quality purchasing decisions based on information received. For example, they could simply discount the perceived quality of products formed on reviews and ratings to obtain a relatively precise estimation of the product quality. Moreover, having a more accurate quality perception could not only improve consumers' welfare but also improve social welfare. A relatively low reference point about the products enables the consumer to have positive gain-loss utility with a higher probability. Thus, there would be a reduced number of product returns, decreasing the costs of returning products such as the opportunity cost of returns and transportation costs. In this way, consumer behaviour could be further investigated to give better strategies to improve the efficiency of the market and total welfare.

6.3. Limitations

There are some limitations of this study. First of all, some of the products do not have the data needed for this study. Besides, since the data collected are all provided by the e-commerce platform, the validity of the data cannot be verified. Moreover, variables related to individual characteristics are not included in the analysis. However, this problem could be solved by surveys, questionnaires, and experiments. In addition, the study is about the largest online retailer in China and may not be representative of consumers using other e-commerce platforms. Nonetheless, policies and the outbreak of the pandemic could affect sales and people's purchasing intentions. Future studies focus on how individual and policy variables affect consumer behaviour when making purchasing and returning decisions may be undertaken.

7. Conclusion

This paper first investigates the formation of quality beliefs based on online reviews and other relevant information. Then using corresponding returns to measure consumer satisfaction after making the purchasing decision.

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There are two major findings. Firstly, when forming quality beliefs, consumers acknowledge the importance of negative reviews and negative review rates have a significant negative effect on sales. Secondly, after consumption, consumers turn out to overestimate the actual quality of the product. Although consumers are fully aware of the importance of negative reviews, the effect of negative reviews cannot counteract the effect of positive reviews. Empirically, consumers underestimate the influence of positive reviews, thus, quality belief is upward biased. Moreover, consumers' decision-making also depends on other behavioural factors such as mental shortcuts, social proof, and sellers' tactics. The findings echo other studies that investigate indirect clues triggering behavioural changes. I analysed the motivation for writing reviews and support the hypothesis that monetary reward is a significant process to request positive reviews according to the theory of reciprocity. The analysis of literature also provides some insights about variations in consumers' expectation formation process.

This paper makes some contributions as well. Firstly, it fills the research gap in the measurement of consumers' evaluation of the actual quality of products. Prior studies on online product reviews focus on the impact of the valence and volume of reviews on consumers' buying decisions. This paper incorporates the investigation of ex-ante and ex-post consumer behaviour regarding purchasing decisions and returning decisions. Moreover, qualitative analysis of the underlying motivations for writing reviews and forming quality beliefs could contribute to the understanding of online consumer behaviours as well.

In addition, the result could provide some insights to buyers. From the buyers' perspective, when making purchasing decisions about online products, the positive impression about the product quality gained from positive reviews needs to be discounted. Moreover, buyers could employ commitment devices to avoid using mental shortcuts and other biased indicators that are mentioned in this paper to form a biased expectation. In this way, there would be improvements in customers' welfare and reduced costs for returning products.

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Appendix 1: Works on Online Reviews and Consumer Behaviour

Year	Author(s)	Data source	Independent variable (Other than valence and volume)	Dependent variable	Findings
2006	Clemons et al.	Ratebeer	Ratings	Sales	Positive reviews improve sales
2006	Chevalier and Mayzlin	Amazon and Barnesandnoble	Text length	Sales	Positive reviews improve sales; High quality reviews matter
2008	Forman et al.	Amazon	Individual characteristics	Sales	Identity-relevant information shapes community members' judgment of products and reviews
2008	Duan et al.	Yahoo, Variety, Box Office Mojo	Ratings	Sales	Box office sales are significantly influenced by the volume of online posting
2008	Li and Hitt	Amazon	Not applicable	Sales	Consumers may not correctly interpreting ratings and making purchases.
2009	Duan et al.	CNET	Ease to get information	Sales	No impact
2010	Chintagunta, Gopinath & Venkataraman	Yahoo and ACNielsen	Not applicable	Sales	Valence of reviews affects sales more than volume of reviews
2011	Archak et al.	Amazon	Textual content	Sales	Textual data change consumer preferences
2012	Sun	Amazon and bn.com	Learning	Sales	Search costs prevent purchasing decision
2012	Yang et al.	Korean Film Council	Not applicable	Sales	The effect of valence is diluted; Volume matters
2012	Lee and Ma	Survey	Gratification	Sales	Reviews raise consumer confidence on buying
2014	Elwalda and Lu	Questionnaires	Risks; consumer attitudes	Sales	Customer trust and intentions increases
2015	Ullrich and Brunner	Online experiment	Negative reviews; Brands	Purchase intention	Brand counteracts negative consumer review
2016	Chong et al.	Amazon	Text sentiment; discount	Sales	Interaction of sentiments, discounts, and volume more significant
2016	Constantinides and Holleschovsky	Consumer reviews platforms & survey	Consumer reliance	Sales	High consumer reliance on review and review format affect purchasing decision
2016	Ren and Nickerson	Amazon and online experiment	Arousal level	Sales	Volume and arousal are more important
2017	Huang et al.	Box Office Mojo	Expert reviews; Peer reviews	Sales	Financial incentives are underestimated
2017	Somohardjo	Questionnaires	Recentness; length	Purchase intention	Positive reviews affect consumer attitude and intentions
2018	Sahoo et al.	North American specialty retailer	Helpfulness; top reviewers	Sales and product returns	More reviews and high-quality reviews lead to less returns; upward biased returns result in more returns
2018	Jia and Liu	Zappos and online experiments	Usefulness	Purchase decision	Positive and highly useful reviews have more adoption rates
2018	Huang et al.	Tmall.com	Recommendation	Sales	With analyse of valence to provide more accurate

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			accuracy; trust		recommendation
2019	Hernandez-Ortega	Online platforms	Product performance	sales	Low performance results in strong negative response of consumer evaluation
2019	Li et al.	Amazon	Sentiment; interact of rating and texts	sales	Numerical rating mediates the effects of textual sentiments
2019	Yi et al.	Experiments	Firm highlighted reviews	Purchasing intention	Highlighted review with high firm reputation affects consumer behaviour
2020	Yin	Experiments	Anger expression	Purchasing	Anger expression more persuasive
2021	Yin et al.	JD.com	Review richness	Sales	High richness strongly affects utilitarian and negative commented products

Appendix 2: Python codes

```
import csv
from selenium import webdriver
from selenium.common.exceptions import TimeoutException
import time
import random
import pandas as pd
import os
import codecs
driver=webdriver.Chrome()
driver.maximize_window()
driver.execute_cdp_cmd("Page.addScriptToEvaluateOnNewDocument",
                 {"source":"""Object.defineProperty(navigator,'webdriver',{get:()=>false})"""})
driver.get("https://www.taobao.com/")
driver.find_element_by_xpath("//*[@id=\"q\"]").send_keys(" keywords ")
time.sleep(random.randint(1, 3))
driver.find_element_by_xpath("//*[@id=\"J_TSearchForm\"]/div[1]/button").click()
time.sleep(random.randint(1, 3))
driver.find_element_by_xpath("//*[@id=\"fm-login-id\"]").send_keys("Username")
time.sleep(random.randint(1, 3))
driver.find_element_by_xpath("//*[@id=\"fm-login-password\"]").send_keys("password")
time.sleep(random.randint(1, 3))
driver.find_element_by_xpath("//*[@id=\"login-form\"]/div[4]/button").click()
time.sleep(10)
driver.find_element_by_xpath("//li/a[contains(text(),\"天猫\")]").click()

#product information
def parse_data():
    divs = driver.find_elements_by_xpath("//div[@class=\"grid g-clearfix\"]/div/div")
    for div in divs:
        mainWindow = driver.current_window_handle
        title = div.find_element_by_xpath(".//div[@class=\"row row-2 title\"]/a").text
        price = div.find_element_by_xpath(".//strong").text
        sale = div.find_element_by_xpath(".//div[@class=\"deal-cnt\"]").text
        href = div.find_element_by_xpath(".//div[@class=\"row row-2 title\"]/a").get_attribute("href")
        posi_counter = 0
        neg_counter = 0
        score1=[0,0,0]
        score2=[0,0,0]
        rate=["","","",""]
        print(href)
        js = "window.open('"+href+"');"
        driver.execute_script(js)
        toHandle = driver.window_handles
        for handle in toHandle:
            if handle == mainWindow:
```


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```
            continue
        mainWindow=toHandle[0]
        driver.switch_to.window(toHandle[0])
        driver.switch_to.window(mainWindow)
        time.sleep(1)
        print("mainWindow:")
        print(driver.title)
        print(driver.find_element_by_xpath("//title"))
        driver.switch_to.window(handle)
        driver.set_page_load_timeout(10)
        driver.set_script_timeout(10)
        try:
            driver.execute_script("window.scrollBy(0,100)");
            driver.find_element_by_xpath("//a[contains(text(),\"评价\")]")
        except:
            driver.execute_script('window.stop ? window.stop() : document.execCommand("Stop");')
        time.sleep(0.1)
        print(":")
        print(driver.title)
        print(driver.find_element_by_xpath("//title"))
        shopdsr1=driver.find_elements_by_xpath("//div[@class=\"shopdsr-item\"]/div[2]")
        shopdsr2=driver.find_elements_by_xpath("//div[@class=\"shopdsr-item\"]/div[2]/span")
        score2[0]=shopdsr2[0].text
        score2[1]=shopdsr2[1].text
        score2[2]=shopdsr2[2].text
        print("description:"+shopdsr2[0].text)
        if shopdsr1[0].get_attribute("class")=="shopdsr-score shopdsr-score-down-ctrl":
            print("lower than average")
            score1[0]=-1
        elif shopdsr1[0].get_attribute("class")=="shopdsr-score shopdsr-score-up-ctrl":
            print("higher than average")
            score1[0]=1
        elif shopdsr1[0].get_attribute("class")=="shopdsr-score shopdsr-score-equal-ctrl":
            print("equals to average")
            score1[0]=0
        print("service:"+shopdsr2[1].text)
        if shopdsr1[1].get_attribute("class")=="shopdsr-score shopdsr-score-down-ctrl":
            print("lower than average")
            score1[1]=-1
        elif shopdsr1[1].get_attribute("class")=="shopdsr-score shopdsr-score-up-ctrl":
            print("higher than average")
            score1[1]=1
        elif shopdsr1[1].get_attribute("class")=="shopdsr-score shopdsr-score-equal-ctrl":
            print("equals to average")
            score1[1]=0
        print("logistic:"+shopdsr2[2].text)
        if shopdsr1[2].get_attribute("class")=="shopdsr-score shopdsr-score-down-ctrl":
            print("lower than average")
            score1[2]=-1
        elif shopdsr1[2].get_attribute("class")=="shopdsr-score shopdsr-score-up-ctrl":
            print("higher than average")
            score1[2]=1
        elif shopdsr1[2].get_attribute("class")=="shopdsr-score shopdsr-score-equal-ctrl":
            print("equals to average")
            score1[2]=0
        time.sleep(1)
        j=0
        #driver.set_page_load_timeout(1)
        #driver.set_script_timeout(1)
        for j in range(0,4):
            try:
```


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```
            driver.find_element_by_xpath("//div[contains(@id,\"ks-overlay-close-ks-component\")]").click()
            break
        except:
            print("")
        time.sleep(0.5)
    j=0
    for j in range(0,3):
        try:
            #driver.execute_script("document.getElementById('side-shop-info').scrollIntoView(true);")
            driver.execute_script("window.scrollBy(0,800)");
            time.sleep(0.1)
            driver.find_element_by_xpath("//a[contains(text(),\"评\")]").click()
            break
        except:
            print("cannot find reviews")
        time.sleep(1)
    if j>=2:
        print("cannot find reviews")
    else:
        time.sleep(1)
        posis=driver.find_elements_by_xpath("//span[@class=\"tag-posi\"]")
        negs=driver.find_elements_by_xpath("//span[@class=\"tag-neg\"]")
        posi_counter = 0
        neg_counter = 0
        print(len(posis))
        print(len(negs))
        for posi in posis:
            print("positive reviews:")
            print(posi.find_element_by_xpath("a").text)
            s_filter = posi.find_element_by_xpath("a").text[posi.find_element_by_xpath("a").text.find("(")+1:posi.find_element_by_xpath("a
").text.find(")")]
            posi_counter=posi_counter+int(s_filter)

        for neg in negs:
            print("negative reviews:")
            print(neg.find_element_by_xpath("a").text)
            s_filter = neg.find_element_by_xpath("a").text[neg.find_element_by_xpath("a").text.find("(")+1:neg.find_element_by_xpath("a"
).text.find(")")]
            neg_counter=neg_counter+int(s_filter)
        print("=================")
        print("positive reviews")
        print(posi_counter)
        print("negative reviews")
        print(neg_counter)
        print("=================")


    time.sleep(4)
    driver.find_element_by_xpath("//div[@class=\"shop-intro\"]/div[@class=\"main-info\"]/a").click()
    #shopdsr1[4].click()
    toHandle = driver.window_handles
    for handle1 in toHandle:
        if handle1 == mainWindow:
            continue
        elif handle1 == handle:
            continue
    driver.switch_to.window(handle1)
    time.sleep(1)
    ratetd = driver.find_elements_by_xpath("//td[@class=\"bg-grayed my-val\"]")
    rate[0]=ratetd[0].text
    rate[1]=ratetd[1].text
    rate[2]=ratetd[2].text
```


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```
        rate[3]=ratetd[3].text
        print("return rates:"+ratetd[0].text)
        print("return span:"+ratetd[1].text)
        print("refund span:"+ratetd[2].text)
        print("WTR:"+ratetd[3].text)
        driver.execute_script('window.close();')
        driver.switch_to.window(handle)
        time.sleep(1)
        driver.execute_script('window.close();')
        time.sleep(0.1)
        driver.switch_to.window(mainWindow)
        time.sleep(0.1)
        #input("enter")
        print(title, price, sale)
        with open("TaoBao.csv", mode="a", encoding="utf-8", newline="") as f:
            csv_writer = csv.writer(f)
            csv_writer.writerow([title, price, sale , posi_counter , neg_counter,score2[0],score1[0],score2[1],score1[1],score2[2],score1[2],rate[0],rate[1],rate[2],rate[3]])
    f = codecs.open("TaoBao.csv",'r','utf8')
    utfstr = f.read()
    f.close()

    #UTF8 to ANSI
    outansestr = utfstr.encode('mbcs')
    f = open("淘宝.csv",'wb')
    f.write(outansestr)
    f.close()
#turn pages
for page in range(0,1):
    time.sleep(random.randint(1,3))
    parse_data()
    time.sleep(random.randint(1,3))
    driver.find_element_by_xpath("//*[@id=\"mainsrp-pager\"]/div/div/div/ul/li[8]/a").click()
```


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