What Makes a Hot Deal? Drivers of Deal Popularity in Online Deal Communities

Completed Research Paper

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Abstract

Online deal communities where members can submit deals offered by firms and where they share information on discounted products are currently enjoying great popularity. However, studies on drivers of deal popularity in these communities are still scarce. Although deal popularity may be attributed to a large extent to the discount price, an extensive investigation of why some deals are voted more favorably than others is still lacking. Addressing this question by analyzing intrinsic and extrinsic deal quality signals, we advance knowledge in three ways. First, we enhance the understanding of the antecedents of human voting behavior in online deal communities building on signaling and social influence theory. Second, we improve the value of deal platforms by providing guidance on which factors determine the deal's value to the community. Third, we provide a model to predict a minimum level of achievable deal popularity in the absence of community members' votes.

Keywords: Online communities, user-generated content, online deals, signaling theory, social mechanisms

Introduction

Online deal communities are currently enjoying great popularity. In these communities, members can submit deals offered by manufacturers or retailers and share information on discounted products. For example, UK's largest site for online deals, HotUKDeals, incorporates 1.2 million subscribers and was placed on number 75 of UK's most visited websites in September 2016 (Alexa 2016a; Faull 2015). Likewise, the German counterpart, mydealz, was placed on number 101 of the most visited websites in Germany (Alexa 2016b). Essentially, there are two major reasons for the popularity of online deal communities.

First, the abundance of price promotions by manufacturers and retailers boosts the growth of online deal communities. Samsung, for example, annually spends around $4.6 billion on marketing activities aimed at increasing sales by distributing coupons and providing discounts (Reed 2013). Price promotions are the most effective marketing tool to increase sales in the short-term (e.g., Eisend 2015; Leeflang and Parreño-Selva 2012), showing a 20 times higher response compared to advertising promotions (Sethuraman and Tellis 1991).

Second, online social communities are important information sources that initiate or simplify consumer purchase decisions (e.g., Cheung et al. 2014; Godes and Mayzlin 2004). Consumers regard opinions and evaluations of other consumers as more credible and trustworthy than firm-generated information (Bae and Lee 2011; Benlian et al. 2012). Hence, they increasingly engage in online social communities and actively share experience and evaluations on products, brands, or retailers with others (Fiedler and Sarstedt 2014; Li et al. 2011). The main purpose of online deal communities is getting firm-independent, genuine advice from other consumers about the best deals (Thompson et al. 2015; Zhang and Jiang 2014). In this respect, they serve many of the same functions as traditional word-of-mouth communications but differ in terms of higher anonymity and higher speed of diffusion (Cheung and Lee 2012; Godes et al. 2005).

The effectiveness of online deal communities hinges crucially on the (perceived) attractiveness of posted deals to its community members. Generally, when users click on a deal link or purchase the offered product, the online deal platform receives a commission. In addition to the comments function, which allows users to express their opinions about deals, many deal communities also incorporate deal popularity (i.e., deal 'hotness') as an overall indicator of how other users evaluate a deal. On the most popular sites, deal popularity is displayed as the difference between the number of 'hot' and 'cold' votes of community members. If offers seem appealing to the community members, the majority will vote the deal hot and it will appear on the deal platform's entry page. Hence, deal popularity signals the deal's value as perceived by community members and can thus influence consumers' purchase decisions by creating a 'bandwagon' effect (i.e., if many people vote a deal hot, it must be a good deal or a good value for money). In fact, there is a positive relationship between deal popularity and consumer purchase likelihood, as signals of popularity help to alleviate quality concerns (Luo et al. 2014; Wang et al. 2013).

However, studies examining the factors that actually determine deal popularity are still very scarce. This especially holds for user-submitted deals, or, in more general terms, the user-generated content context (Scholz et al. 2013; Yadav and Pavlou 2014; Zhang and Jiang 2014). Prior work has focused on deals provided by retailers or platform operators (as in the case of Groupon) or on the popularity of online sellers (Ou and Chan 2014). However, online deal communities are distinct as they only allow genuine consumers, who are not involved in promotional activities, to contribute deals.

Intuitively, deal popularity can be attributed to a large extent to the discount price. However, high discounts, although often appealing to price-sensitive consumers, might also raise concerns about the underlying product quality (Ba and Pavlou 2002). Previous research shows that with increasing discount magnitude the sales volume may decrease (Cao et al. 2015). In addition, discount price alone might not be sufficient for judging the attractiveness or value of the deal, and consumers might search for additional information cues, such as reputation of the deal creator, to form their evaluations.

Hence, this study seeks to get a better understanding of the drivers of popularity of user-generated deals in online deal communities. In particular, building on quality signaling and social influence theory, we develop a research model for explaining deal popularity and empirically test it on a sample of user-generated deals for two product categories obtained from mydealz, which is the German equivalent of

HotUKDeals (see Figure 1). In line with quality signaling theory (Akerlof 1970), we identify different deal characteristics as quality signals that help to alleviate uncertainty and thus allow users to assess a deal's underlying value. More specifically, we differentiate between intrinsic quality signals that refer to the deal content and the deal creator, and extrinsic quality signals that refer to information from external sources. 'Intrinsic cues' are more easily accessible as they are directly available on the deal's page, whereas 'extrinsic cues' are associated with higher processing effort, since individuals have to engage in additional search to obtain them (Anderson et al. 1979; Beatty and Smith 1987).

Figure 1 shows an example for a popular deal in a major online deal community, HotUKDeals. Various attributes (i.e., intrinsic quality signals) appear on the deal page representing deal and deal creator characteristics as well as product and retailer information. On the left top corner, the deal popularity score represents the difference between hot and cold votes for a deal. Community members are allowed to vote once per deal. The deal title contains a short product description, the retailer name, and the product's deal price. Below is information about the deal creator and a link to his or her profile which includes the user's membership details and information whether the user is appointed by the deal platform (i.e., a professional 'deal scout') or a regular user. The deal description below may contain information on the start and the end of the deal, a product description, a reference price (based on price comparison sites), information about the retailer or shipping costs, etc. The total number of comments on the left bottom of the figure displays all comments referring to the deal.

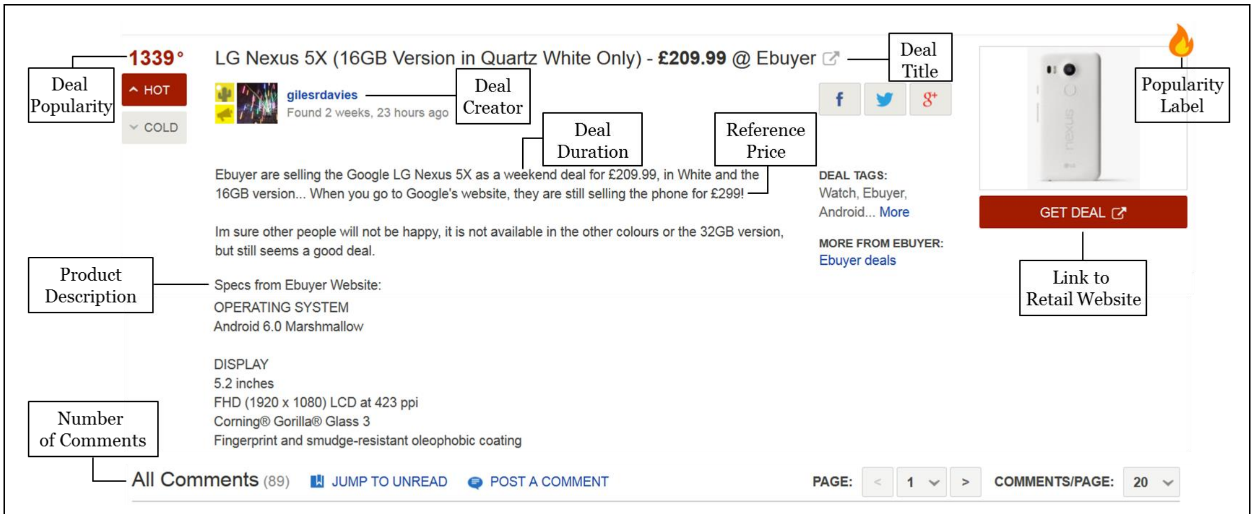

Figure 1. Example of a Popular Deal

We advance both theoretical and practical knowledge on online social communities in three ways. First, we enhance the understanding of human voting behavior in online deal communities building on signaling and social influence theory. Second, we improve the value of online deal platforms by providing guidance of which factors determine the deal's value to the community. Consumers would have lower incentives to search for additional information elsewhere in order to reduce their uncertainty about the discounted product. Hence, user satisfaction and retention rates would increase. Our model can be used to predict a minimum level of achievable popularity of online deals that have not received any votes yet. Each new deal could be assigned a predicted score and the deal creator would receive instant feedback on how the posted offer might be evaluated by the community members and what could be improved. Finally, our results are also relevant for manufacturers and retailers as they provide valuable insights into how to design effective price promotions.

We organize the remainder of this paper as follows: In the next section, we outline the conceptual background discussing key concepts and related literature, and present the research framework. Then, we develop our hypotheses. Next, we describe our research methodology including data collection, variable operationalization and regression analysis. Subsequently, we report the results and provide a robustness check. Finally, we discuss the results of our study and provide managerial and research implications.

Conceptual Background

Online Social Communities

Online or virtual social communities facilitate information-sharing among participants and maximize the knowledge base of the community members. In line with Gopal et al. (2006), we examine online communities that focus on sharing various promotional deals for consumer products and thereby rely primarily on user-generated content. As opposed to social commerce or group-buying websites, such as Groupon, where retailers or manufacturers directly promote discounted products, deal communities are not formally organized within the firm-controlled system (Libai et al. 2010). Hence, deals are posted by genuine community members. Other members of the deal community can vote on the deals to express their perception of the deal's value or desirability. The best voted deals (i.e., hottest deals) are then prominently displayed at the front page of the deal platform.

Dholakia et al. (2004) distinguish seven motives for participation in online social communities. In particular, information value (i.e., getting and sharing information), instrumental value (i.e., solving a problem, generating an idea, influencing others), and social enhancement (i.e., gaining acceptance and approval of other members) play a key role in the context of online deal communities. Other reasons to participate in online deal communities relate to smart-shopper feelings and the price mavensim motive: Shoppers attribute the causes for obtaining a deal to internal factors. This is expressed in so called smart-shopper feelings, when consumers feel efficient and savvy for saving money and getting a good deal (Schindler 1989). In addition, research on behavioral aspects of pricing has introduced the concept of price mavenism as the "degree to which an individual is a source for price information for many kinds of products and places to shop for the lowest prices, initiates discussions with consumers, and responds to requests from consumers for marketplace price information" (Lichtenstein et al. 1993, p. 235).

Liang et al. (2011) indicate that social support and platform quality positively affect users' participation and subscription rates in online social communities. Mutual trust among community members increases their loyalty toward the online platform (Chen et al. 2009). However, mutual trust can be undermined by anonymity, a predominant characteristic in the online context (Guadagno et al. 2013). In the light of high uncertainty and insufficient information, users might seek for signals or additional cues to ascertain product quality and deal trustworthiness, and thus to enhance decision confidence (Ba and Pavlou 2002; Wells et al. 2011).

Quality Signals in Online Deal Communities

Signaling theory suggests that quality signals can reduce information asymmetry between two or more parties, such as members of online social communities (e.g., Cheung et al. 2014; Connelly et al. 2011; Kirmani and Rao 2000). Li et al. (2009), for example, use signaling theory to explain consumers' participation and bidding decisions in Internet auctions. At this, they classify Internet auction characteristics into auction quality and seller credibility indicators, and examine how different consumers react to these indicators. Luo et al. (2012) indicate that signals of retailer credibility, such as retailer service quality or a well-designed website, can mitigate negative effects of product uncertainty on customer satisfaction. Kuan et al. (2014) and Lee et al. (2015) find that information on Facebook likes increases the intention to purchase a deal as well as actual Groupon sales. Ou and Chan (2014) focus on electronic markets and identify institutional-based quality signaling mechanisms (such as the seller's reputation and consumer protection schemes) and social-based quality signaling mechanisms (such as the seller's virtual presence as well as shop and product tagging).

While previous research has thus investigated quality signaling mechanisms in the context of Internet auctions or online shops, an empirical investigation of the effects of quality signals in the context of online deal communities is missing. However, given the specificities of the latter with respect to the roles of information asymmetry and trust, it is important to examine whether the current design of deal communities helps to increase trust among community members and to alleviate uncertainty in community members' evaluations of deal value. More specifically, *we examine the drivers of deal popularity (expressed as the difference between the number of hot and cold votes)* in online deal communities. Deal popularity signals a deal's value to the community, its desirability, and hence the users' purchase intentions (Luo et al. 2014).

We examine which factors contribute to a deal's popularity, or, in other words, which information cues users rely on to evaluate a deal's value and to vote on its popularity. In line with former studies (e.g., Li et al. 2009; Ou and Chan 2014), we rely on a two-sided classification of quality signaling mechanisms. In particular, we differentiate between '*intrinsic cues*' and '*extrinsic cues*' (see Figure 2). The former represent quality signals that are directly visible on the deal page and thus provide easily accessible information about a deal's value (see Figure 1). In particular, intrinsic cues relate to the deal content (deal price, discount magnitude, number of comments, product description, shipping costs amount, and deal duration) and the deal creator (whether the community member is a deal scout or not). In various online deal communities, users can be distinguished into regular users and professional deal scouts, that is, users appointed by the deal platform searching for the best deals independent of sellers (i.e., manufacturers or retailers).

Extrinsic cues are obtained from external sources (e.g., product quality ratings at Amazon), which means that they serve as additional proxy variables mitigating uncertainty. Since it might be difficult to ascertain the quality and value of the discounted product solely based on the information provided by the deal creator (i.e., the deal's content), users might seek for additional information about the product or the seller (Gu et al. 2012). This especially applies in the absence of detailed product or seller information in the deal description. In line with former studies (e.g., Sen and Lerman 2007), we assume that consumers are likely to incorporate these additional cues in their evaluations that signal product quality and popularity, such as the quality rating and total number of ratings on Amazon, or retailer reputation, for example, on price comparison sites.

Social Influence

In this study, social influence describes the extent to which members of online deal communities influence one another's behavior to conform to the community's behavioral patterns (Venkatesh and Brown 2001). Observing that many other users voted or commented on deal popularity is likely to affect the respective user evaluations of the deal value and thus their purchase decisions (Lee et al. 2011). The so-called 'bandwagon' effect describes this tendency to follow the behavior of others and accept the information from others as real evidence (Burnkrant and Cousineau 1975; Leal et al. 2014). The phenomenon of bandwagon effect has been largely addressed in previous research. It occurs, for example, when purchases are positively correlated across individuals (Miller et al. 2009), or, in the context of online word-of-mouth, when subsequent consumers post similar opinions expressed in previous product reviews (Moe and Schweidel 2012). Hence, social influence leads to conformity, which involves a change in attitudes and behaviors (Kuan et al. 2014). In the course of this study, social cues like comments by other community members might largely determine deal popularity.

Figure 2 summarizes our research framework that differentiates between intrinsic and extrinsic quality signals in online deal communities.

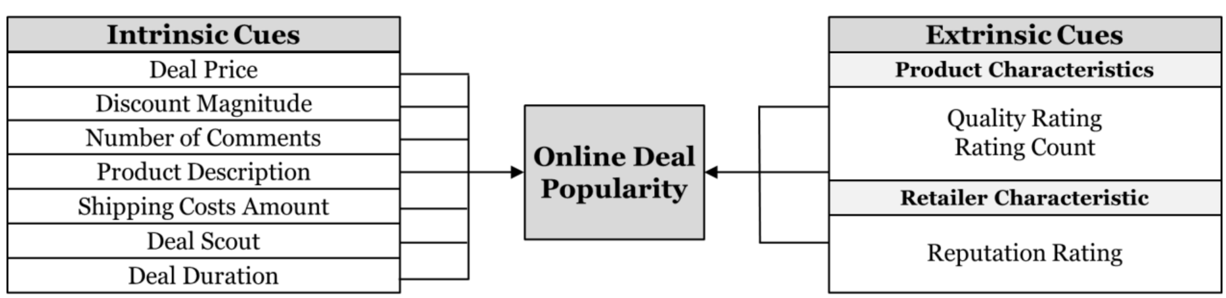

Figure 2. Research Framework

Hypothesis Development

In the following, we develop hypotheses regarding the impact of quality signals, that is, intrinsic and extrinsic cues in online deal communities that should affect deal popularity as outlined in Figure 2.

Intrinsic Cues

Deal Price and Discount Magnitude

The price of a product (and thus the price of a deal) generally plays a dual role in consumer evaluations (Völckner 2008). First, the price represents a monetary sacrifice for consumers to satisfy their consumption needs. Hence, some previous research suggests that price negatively affects purchase probabilities (Erickson and Johansson 1985). In this respect, Song et al. (2016) show that more expensive products are generally less popular in the online deal context. However, price has a second informational role in terms of a signal for product quality. In this respect, Ba and Pavlou (2002) find that consumers in electronic markets perceive higher prices as an indication of high product quality. Furthermore, setting the price of a product above the competing products' prices attracts more quality-conscious consumers (Kayhan et al. 2010).

Accordingly, we suggest that if the deal's price is below a certain price level or threshold, the discounted product is perceived as 'too cheap' to be of good quality; if the price is above a certain price level or threshold, the product is perceived as 'too expensive' due to the high perceived monetary sacrifice (Dodds 1995; Dodds et al. 1991). As deal price increases, users' perceptions of a deal's value should thus first increase, but then decrease after a certain optimum value has been reached. Hence, we propose a quadratic (inverted-U) relationship between deal price and deal popularity.

H1a: The relationship between deal price and online deal popularity is quadratic and has an inverted-U-shape.

We define discount magnitude as the *absolute* difference between the deal price and the reference price posted by the deal creator. In general, when consumers are confronted with deal prices, price information processing may vary from challenging the price, followed by extensive research, to uncritical price acceptance (Hamilton and Chernev 2013). In online deal communities, deal prices and reference prices are posted by firm-independent users (Zhang and Jiang 2014). In addition, online deal communities claim that any type of advertisement or self-promotion is regarded as abuse and dealers involved will be suspended (e.g., HotUKDeals). Hence, there is no further need for consumers to use, for example, price comparison websites to further validate the reference price cited by the deal creator. We thus suggest that users will rely on the deal and the reference price to evaluate the resulting monetary savings and we measure discount magnitude accordingly.

Previous research provides mixed evidence regarding the impact of discount magnitude on deal popularity. Cao et al. (2015) show that a larger discount percentage, displayed as savings compared to the original price, results in a decrease of Groupon sales. However, the majority of studies reveal a positive effect of discount magnitude on deal popularity (e.g., Eisenbeiss et al. 2015; Luo et al. 2014; Song et al. 2016). In line with the majority of findings, we formulate the following hypothesis:

H1b: Online deal popularity increases with discount magnitude.

Number of Comments

Referring to social influence theory, dynamics in online deal communities may lead to bandwagon effects (e.g., Lee et al. 2011; Miller et al. 2009). Kuan et al. (2014) find that the number of comments can exert normative social influence on the opinions of other users. Social 'buzz' or word-of-mouth linked to specific deals may signal that it is worth talking about the deal and thus should attract attention of other community members.

In addition, opinion-based social information in the form of online word-of-mouth can serve as a signal of product quality that drives sales of various consumer products (Amblee and Bui 2011; Gu et al. 2012). In this respect, a high number of community member comments can help to reduce uncertainty about a deal's value (Dimoka et al. 2012; Li et al. 2011; Mudambi and Schuff 2010; Pavlou and Dimoka 2006). Hence, we propose that:

H2: Online deal popularity increases with the number of member comments.

Deal Description

The availability of product-related information decreases both uncertainty and necessity of further online search (Granados et al. 2012; Li et al. 2014). In the context of online deal communities, missing information regarding product quality hinders consumers to comprehensively evaluate a deal's value. Consumers are forced to search elsewhere for information on the product. However, obtaining additional cues for evaluating a product's fit to one's preferences is associated with additional cognitive effort (Aydinli et al. 2014). This leads to the following hypothesis:

H3a: Online deals that include a detailed product description have higher popularity than online deals that lack a detailed product description.

In addition to the detailed product description, the shipping costs should play a crucial role when it comes to deal integrity and attractiveness. Additional shipping costs increase deal price complexity and thus decrease perceived transparency of how the end price is calculated (Homburg et al. 2014). Lewis et al. (2006) find that consumers react strongly to shipping costs. More specifically, consumers are approximately twice as sensitive to changes in shipping costs as they are to changes in product price (Smith and Brynjolfsson 2001). Higher shipping costs are associated with higher monetary sacrifice to obtain a product. We therefore derive the following hypothesis:

H3b: Online deal popularity decreases with the amount of shipping costs.

Deal Scout

When it comes to uncertainty about a deal's value, online deal community members may also rely on deal creator signals. In accordance with social influence theory, Park and Kim (2008), and Cheung et al. (2014) reveal a moderating role of consumer expertise in determining the impact of online word-of-mouth on consumer purchase decisions.

Forman et al. (2008) show that identity-relevant information about reviewers affects online community members' judgment of products and reviews. Based on Chen and Xie (2008) who distinguish consumer reviewers and professional reviewers, we identify two groups of deal creators. We differentiate between deal creators appointed by the community provider (i.e., professional deal scouts with a strong price mavenism motive) and regular members. This information is given in the respective community member's user profile and indicates whether the user has high experience in searching deals. Evidence from both signaling and social influence theory leads to the following hypothesis:

H4: Online deals posted by deal scouts have higher popularity than online deals posted by regular users.

Deal Duration

In line with Eisenbeiss et al. (2015) and Luo et al. (2014), we also *control for* the effects of deal duration. We assume a positive relationship between the number of deal days and its popularity as more votes can be accumulated over time. Hence, we propose that:

H5: Online deal popularity increases with deal duration.

Product Characteristics

The literature shows that both high quality rating on Amazon (e.g., Chevalier and Mayzlin 2006; Floyd et al. 2014) and total number of ratings on Amazon (e.g., Cui et al. 2012; Jang et al. 2012) are important to consumers. Both serve as cues to reduce uncertainty about product quality (Dimoka et al. 2012; Mudambi and Schuff 2010) and increase the expected fit to one's preferences (Dorner et al. 2013; Li et al. 2011). At this, product ratings essentially emerge as evidence of social proof (Cialdini 2001), and consumers are more likely to prefer a product that has acquired substantial social validation. In this respect, a high quality rating value conveys a positive product image of product by other consumers who rated it.

Although information about Amazon ratings is not included in every deal description, the quality rating and the count of product ratings on Amazon can serve as proxy variables regarding the quality and popularity of a product. We thus propose that:

H6a: Online deal popularity increases with the product's quality rating.

H6b: Online deal popularity increases with the product's rating count.

Retailer Characteristics

Along with price and product information, a retailer's reputation is an important quality signal when it comes to consumers' purchase decisions (Ba and Pavlou 2002; Chu et al. 2005; Smith and Brynjolfsson 2001). Bodur et al. (2015) reveal a significant indirect effect of the retailer rating on the perceived price attractiveness through consumers' price validity perceptions. As information about the retailers' reputation is not present in every deal description, the retailers' reputation rating on a leading German price comparison site, Geizhals, serves as a proxy in our model. Being a signal for retailer reputation, we propose that:

H7: Online deal popularity increases with the retailer's reputation rating.

Methodology

Data Collection and Sample

We collected data on *completed* deals posted between September 2015 and March 2016 on a major online deal community mydealz.de, which is the German equivalent to HotUKDeals.com (see Figure 1). Founded in 2007, the online community has now about 500,000 members and records more than 58,000 deal offers. We obtained information on completed deals for two product categories: 289 smartphones, and 315 DVDs & Blu-rays, resulting in a total sample of 604 observations. To avoid systematic bias in sampling, we collected all deals that were recorded for the two product categories in the time span mentioned above. We had to exclude deals lacking information on deal duration and reference price to ensure robust estimation of the drivers of deal popularity. Further, we filtered out all vouchers, coupons, and promotional codes, whose redemption followed specific rules, and that hence were not available for all deal community members. We decided to collect deals on these two product categories as (1) they offer the most comprehensive data base, (2) they have fairly distinct (deal) price levels, and (3) they are distinct in terms of a predominance of utilitarian (smartphones) and hedonic attributes (DVDs & Blu-rays), thus making it possible to examine how the effects of different drivers of deal popularity might vary depending on the product category.

For each deal, we captured its popularity degree, which is displayed on mydealz.de as the absolute difference between the number of hot and cold votes. We also recorded the deal's discounted price, deal duration in days, deal creator status (if the creator is a deal scout or a regular user) and the number of comments. From the deal description we extracted the reference price, based on which we computed a deal's discount magnitude, and the amount of shipping costs. We further recorded whether the deal description contained information about the product and its characteristics. To measure the effect of extrinsic cues which users might rely on to ascertain a product's quality and popularity (i.e., how many other consumers purchased the product), we obtained information on each product's quality rating and total number of ratings from Amazon.de. Finally, we collected information on reputation ratings of retailers from Geizhals.de, a leading German price comparison site. Table 1 provides summary statistics for the variables included in the analysis.

Table 1. Descriptive Statistics of Our Sample (n=604)									
Variable	Description	Smartphones (n = 289)				DVDs & Blu-rays (n = 315)			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Deal Popularity	Difference between the number of hot and cold votes for each deal	280.491	359.693	-370	2179	313.140	249.192	-185	1152
Deal Price	Deal price of a product (in €)	246.081	156.199	39.99	777	24.873	20.464	1.99	119.88
Discount Magnitude	Difference between the deal's price and the cited reference price (in €)	33.898	27.752	1.61	200	11.082	12.973	0.05	91.03
Number of Comments	Total number of comments for each deal	36.751	57.346	1	534	19.527	17.624	0	122
Product Description	Dummy variable indicating if a detailed product description is included in the deal text (1 = product description included, 0 = otherwise)	0.841	0.366	0	1	0.683	0.466	0	1
Shipping Costs Amount	Amount of shipping costs for the product	1.154	2.040	0	12.99	0.545	1.298	0	6.99
Deal Scout	Dummy variable indicating if the deal creator is appointed by the deal platform as a deal scout (1 = deal scout, 0 = otherwise)	0.273	0.446	0	1	0.337	0.473	0	1
Deal Duration	Duration of a deal (in days)	2.820	2.977	1	22	3.683	4.182	1	25
Product Quality Rating	Average Amazon.de rating for each product reported until the day of the deal	4.018	0.552	2	5	4.358	0.421	2.10	5
Product Rating Count	Number of Amazon.de ratings for each product reported until the day of the deal	166.637	239.208	1	2258	224.660	312.376	1	2540
Retailer Reputation Rating	Average rating of a retailer offering a discounted product, collected from Geizhals.de	3.877	0.531	1.5	4.85	3.798	0.453	2.06	4.42

The descriptive statistics for the two product categories exhibit several interesting patterns. In particular, compared to smartphones DVDs & Blu-rays feature much fewer deals with a negative popularity score ($\chi^2 = 11.679, p < 0.01$), and do not have any deals that accumulated more than 200 cold votes.[1] This observation can be attributed to the hedonic nature of DVDs & Blu-rays to satisfy consumers' emotional or sensual needs. Individuals tend to vary in their evaluations of utilitarian vs. hedonic products (Hirschman and Holbrook 1982; Batra and Ahtola 1991). While in case of smartphones, users base their judgments on objective or utilitarian criteria (e.g., the product's price as well as the ability to perform a useful function or accomplish a practical task), users' judgments of DVDs & Blu-rays are based on subjective criteria, like taste and preference match. So, there will be a stronger deviation in consumer evaluations of the (actual) deal value for DVDs & Blu-rays than for smartphones. Another reason could be that the purchase of smartphones is usually associated with higher expenses resulting in higher perceived risks of a wrong purchase decision (Völckner 2008). So, community members might engage to a greater extent in voting on online deals for expensive products to warn others from the costly payment. This is also evidenced by a significantly higher number of comments submitted to the deals for smartphones than for DVDs & Blu-rays ($Welch's\ t = 4.91, df = 337.75, p < 0.01$).

Evaluating the quality and the preference match of discounted products is usually difficult and requires additional or extrinsic information cues like product or retailer ratings. While both product categories feature mostly positive Amazon ratings with the average number of stars greater than 4, which is consistent with previous research highlighting the predominance of positive ratings on Amazon (Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2011); DVDs & Blu-rays, however, are characterized, on average, by much larger number of total ratings than smartphones ($Welch's\ t = -2.58, df = 583.69, p < 0.01$). One possible explanation is that many DVDs & Blu-ray deals promote movies that were very popular at the time of posting (i.e., blockbusters), and were therefore characterized by more purchases and subsequently higher rating counts on Amazon.de compared to smartphones.

Analysis

The dependent variable, deal popularity, is defined as the absolute difference between the number of hot and cold votes for a deal and hence scaled in [-∞, ∞]. We assume that the relationship between the deal popularity and its determinants is best estimated by a linear model. To evaluate our research model, we ran a heteroscedasticity-robust OLS regression (MacKinnon and White 1985) for each product category, which is summarized by the following equation:

$$\begin{aligned} DealPopularity = {} & \beta_0 + \beta_1 DealPrice + \beta_2 DealPrice^2 + \beta_3 DiscountMagnitude + \beta_4 NumberComments \\ & + \beta_5 ProductDescription + \beta_6 ShippingCostsAmount + \beta_7 DealScout + \beta_8 DealDuration \\ & + \beta_9 QualityRating + \beta_{10} RatingCount + \beta_{11} RetailerReputation + \epsilon \end{aligned}$$

Since the dependent variable *Deal Popularity* is left-skewed (i.e., most deals were rated positively by community members), the effects on the conditional mean as estimated with on OLS regression might be biased. Thus, we also performed a quantile regression and estimated the effects on the conditional median as an additional robustness check (see section Robustness Check) which is more robust to skewed data and outliers. The results of OLS and quantile regressions are largely consistent (in terms of both magnitude and statistical significance), indicating that despite the skewness of deal popularity OLS yields reliable estimates. The underlying correlation matrices are presented in Appendix A.

As baseline, we computed a model that only involves the cues observable on the deal's page (i.e., intrinsic cues (see Figure 1.). We then computed an extended model by adding extrinsic cues obtained from external sources, such as average Amazon rating and total number of Amazon ratings for each product as well as retailer reputation rating on Geizhals.de. Since the valuation of a particular product can vary

[1] On mydealz.de, if a deal accumulates 200 or more hot votes, it gets assigned the popularity label 'on fire' (see Figure 1); however, if it accumulates 200 or more cold votes, it becomes the label 'frozen'. Such popularity labels should serve as clear quality signals allowing to identify 'good' from 'bad' deals.

across individuals, Amazon ratings as well as seller reputation ratings were centered on the mean values. Comparing the two models allows us to evaluate whether the extrinsic cues can provide (significant) additional explanation power to what determines online deal popularity. In other words, we can evaluate to what extent deal community members incorporate extrinsic cues in their assessments of a deal's value. We compared the regression models with Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), which indicate how much more (less) information is lost by the baseline (intrinsic cues) than by the expanded model (intrinsic + extrinsic cues) (Burnham and Anderson 2004).

Results

The results in Table 2 demonstrate that including extrinsic cues significantly improves the goodness-of-fit of the research model for DVDs & Blu-rays. The expanded model indicates better AIC and BIC and explains more variance in the dependent variable, as expressed by higher R^2. In contrast, extrinsic cues do not significantly contribute to the explanation of online deal popularity of smartphones, as indicated by worse AIC, BIC and very slight improvement of R^2.

Effects of Intrinsic Cues

For both smartphones and DVDs & Blu-rays we find a quadratic (inverted-U) relationship between *Deal Price* and deal popularity (H1a). This result is consistent with previous research (Dodds 1995; Dodds et al. 1991) and suggests that users attribute higher deal prices to higher underlying product quality. As deal price increases, users' perceptions of a deal's value also increase, but then decrease when the deal price exceeds the acceptable price limit.

Discount Magnitude has a positive and statistically significant effect on deal popularity of smartphones, but is statistically insignificant for DVDs & Blu-rays (H1b). Online deal community members seem to rely on reference prices as cues for calculating the resulting monetary savings and for assessing the value of the deal, especially in the case of more expensive products such as smartphones. An increase in discount magnitude by 1 euro leads to an increase of deal popularity by 2 hot votes. Since DVDs & Blu-rays are generally less expensive and are hence characterized by lower discount magnitudes than smartphones (as also conveyed by descriptive statistics in Table 1), it seems plausible that users rather rely on the deal price and other cues to substantiate the value of the deal. Hence, H1b is only supported for smartphones.

The positive and highly statistically significant effect of the *Number of Comments* provides support for the bandwagon effect postulated by H2 and is in line with previous studies' results based on social influence theory (e.g., Kuan et al. 2014). Deals receiving a large number of comments generate more attention and create more social buzz within the community than deals without comments or with a small number of comments. Comments are also perceived as valuable cues providing additional information that might be obscured in the description of the deal. Interestingly, the effect size of comments for smartphones is significantly smaller in absolute value compared to DVDs & Blu-rays ($z = -4.697, p < 0.01$).

Product Description has a significant positive effect on deal popularity of smartphones, but is statistically insignificant for DVDs & Blu-rays (H3a). The coefficient of 87.048 implies that deals providing detailed information on smartphones accumulate about 87 more hot votes than deals without detailed product description. In case of DVDs & Blu-rays, it is plausible to assume that users obtain information on the content of the DVD/Blu-ray from external sources. For example, they might consult expert critiques, user reviews, or engage in discussions with other community members (as indicated by the strong impact of the *Number of Comments* on deal popularity).

Shipping Costs Amount significantly affects deal popularity of DVDs & Blu-rays, suggesting that an increase in the amount of a product's shipping costs leads to a decrease in deal popularity (H3b). Taking into account that DVDs & Blu-rays are generally characterized by low prices (M=24.873, SD=20.464), a 1 euro increase in shipping costs might substantially reduce the expected savings. Our results show evidence for this effect. An increase of the shipping costs by 1 euro is equivalent to a loss of 15 hot votes. On the other hand, the amount of shipping costs does not affect the popularity of smartphone deals (given the much higher average price of smartphones).

Table 2. Regression Results for Research Model								
	Smartphones				DVDs & Blu-rays			
	Intrinsic Cues		Intrinsic +Extrinsic Cues		Intrinsic Cues		Intrinsic Cues + Extrinsic Cues	
		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.
Intercept	-144.834** (69.308)		-159.631** (75.812)		36.364 (35.677)		45.203 (35.662)	
Deal Price	0.933*** (0.360)	0.405	0.898** (0.360)	0.390	2.218* (1.273)	0.182	1.104 (1.351)	0.091
Deal Price²	-0.002*** (0.0005)	-0.5306	-0.002*** (0.0005)	-0.521	-0.035*** (0.013)	-0.244	-0.025* (0.014)	-0.172
Discount Magnitude	2.025*** (0.665)	0.156	2.072*** (0.669)	0.160	-0.163 (1.057)	-0.008	0.014 (1.079)	0.001
Number of Comments	4.017*** (0.874)	0.640	4.024*** (0.867)	0.642	10.958*** (1.245)	0.775	10.646*** (1.238)	0.753
Product Description	87.048** (36.615)	0.089	93.966** (39.208)	0.096	24.406 (21.641)	0.046	25.830 (20.519)	0.048
Shipping Costs Amount	-3.706 (5.623)	-0.021	-1.866 (5.367)	-0.011	-14.939** (6.922)	-0.078	-13.526** (6.833)	-0.070
Deal Scout	165.486*** (34.134)	0.205	162.077*** (33.604)	0.201	79.333*** (18.089)	0.151	71.534*** (18.735)	0.136
Deal Duration	5.594 (5.046)	0.046	5.431 (4.991)	0.045	2.845 (2.299)	0.048	2.975 (2.099)	0.050
Product Quality Rating			-8.030 (20.482)	-0.012			90.645*** (23.744)	0.153
Product Rating Count			0.065 (0.052)	0.043			0.057* (0.031)	0.071
Retailer Reputation Rating			26.513 (27.876)	0.039			-5.293 (18.087)	-0.010
N	289		289		315		315	
R²	0.650		0.653		0.617		0.639	
AIC	3937.329		3940.773		4087.347		4074.338	
BIC	3973.993		3988.436		4124.873		4123.121	
Notes: robust standard errors are listed in parentheses *p<0.10, **p<0.05, ***p<0.01 (two-tailed tests)								

Our results also confirm that the *Deal Scout* status has a positive effect on the popularity of posted deals (H4). The regression estimates suggest that the deals posted by users appointed by the platform provider to search for hot deals accumulate for smartphones about 165 and for DVDs & Blu-rays about 79 more hot votes than deals posted by regular community members. We also re-run regressions using other characteristics relating to deal creator. For instance, instead of deal scout status we included the number of comments a deal creator submitted before the respective deal. The results are similar to those presented above: all the signs of the coefficients remain the same as predicted, except that the coefficient magnitudes for DVDs & Blu-rays as well as the predictive power of the model are somewhat smaller than in the model presented. Specifically, R-square decreases by 2%, AIC and BIC worsen by about 3%, respectively. The goodness-of-fit measures for smartphones remain practically the same.

The effect of *Deal Duration* is not statistically significant, indicating that there is no relationship between the amount of days a deal lasts and its popularity. Hence, H5 is rejected.

Effects of Extrinsic Cues

In Table 3 column 2 and column 4, we present the extended models including variables for a product's average quality rating and the total number of ratings (on Amazon.de), as well as the retailer's reputation rating (on Geizhals.de). Both *Product Quality Rating* and *Product Rating Count* have significant positive effects on deal popularity of DVDs & Blu-rays. This result indicates that users are more inclined to vote favorably on deals for products of high perceived quality (as conveyed by high average quality rating) and that have been purchased more frequently and consequently received high social acclaim (as conveyed by high number of ratings). Thus, a one star-improvement in the average quality rating results in an increase of deal popularity by about 91 hot votes, and each additional rating leads to an increase of deal popularity by 0.50 votes.

The effects of *Product Quality Rating* and *Product Rating Count* are, however, not significant for smartphones, suggesting that users' perceptions of a deal's value for this product category are rather affected by the perceived resulting savings and other intrinsic cues included in the deal content, such as a detailed product description. Hence, H6a and H6b are only supported for DVDs & Blu-rays.

The effect of *Retailer Reputation Rating* on deal popularity is insignificant for both product categories (H7), which indicates that users do not incorporate signals of retailer reputation in their evaluations of a deal's value.

Robustness Check

As a robustness check, we computed a quantile regression with heteroscedasticity-robust standard errors (Koenker 2005). Given that the dependent variable, deal popularity, is left-skewed, OLS can provide biased and inconsistent estimates.

The results of a quantile regression are generally consistent (in terms of both magnitude and statistical significance) with the results of OLS reported above (see Table 3), except that the effect of *Shipping Costs Amount* is not significant in the extended model for DVDs & Blu-rays. Hence H3b can only be partially accepted in this case. Interestingly, the effect of *Retailer Reputation Rating* is positive and statistically significant for smartphones, suggesting that users, indeed, to some extent, incorporate the signals of retailer reputation in their evaluations of the deal's value. Hence, H7 is partially supported for smartphones.

Additionally, we also ran a regression for the pooled data set, by combining the data of both product categories. To control for the category-specific effects, an idiosyncratic random-intercept ψ_i was added in the model. It was estimated with a restricted maximum likelihood estimator (REML) based on the following equation:

$$y_i = \alpha + X_i\beta + (1|\psi_i) + \epsilon_i,$$

where X_i represent a set of deal's i characteristics, the terms α, β are parameters to be estimated and ϵ_i captures the error term. The results are reported in Appendix B.

They are largely consistent with the regression results for each product category reported in Table 3. All the signs of the coefficients remain the same as predicted, except that coefficients on *Shipping Costs Amount* and *Product Description* are not significant for the pooled data set. Notably, the effect of *Deal Duration* becomes statistically significant. A positive coefficient sign indicates that deal popularity increases with the deal duration, as more votes are accumulated over time, which in turn boosts the deal popularity. Improvements in pseudo R^2 as well as AIC and BIC suggest that the extended model including both intrinsic and extrinsic cues better explains deal popularity of both product categories.

Table 3. Quantile Regression Results for Research Model ($\tau = 0.50$)

	Smartphones				DVDs & Blu-rays			
	Intrinsic Cues		Intrinsic Cues + Extrinsic Cues		Intrinsic Cues		Intrinsic Cues + Extrinsic Cues	
		Std. Coef.		Std. Coef.		Std. Coef.		Std. Coef.
Intercept	-45.923 (46.688)		-122.472* (47.746)		16.814 (29.611)		20.269 (27.110)	
Deal Price	0.287 (0.201)	0.125	0.429** (0.196)	0.186	3.353** (1.568)	0.275	2.136 (1.430)	0.175
Deal Price²	-0.001** (0.0003)	-0.230	-0.001*** (0.0003)	-0.316	-0.051*** (0.019)	-0.347	-0.038** (0.016)	-0.268
Discount Magnitude	0.907*** (0.291)	0.070	1.291*** (0.318)	0.100	-0.997 (0.741)	-0.052	-1.053 (0.857)	-0.055
Number of Comments	6.112*** (0.747)	0.974	5.984*** (0.726)	0.954	11.891*** (1.106)	0.841	11.839*** (1.128)	0.837
Product Description	46.184 (35.689)	0.047	93.253** (39.577)	0.095	13.693 (19.057)	0.026	18.617 (16.822)	0.035
Shipping Costs Amount	-5.306 (3.274)	-0.030	-1.465 (4.285)	-0.008	-10.335* (5.748)	-0.054	-8.142 (6.639)	-0.042
Deal Scout	105.580*** (12.720)	0.131	109.316*** (31.065)	0.136	69.662*** (18.496)	0.132	69.896*** (16.091)	0.133
Deal Duration	5.518*** (1.491)	0.046	5.167** (2.094)	0.043	0.520 (2.068)	0.009	1.248 (2.217)	0.021
Product Quality Rating			6.192 (8.932)	0.010			83.106*** (17.256)	0.140
Product Rating Count			0.051 (0.062)	0.034			0.038* (0.021)	0.048
Retailer Reputation Rating			32.321*** (11.653)	0.048			-11.180 (16.415)	-0.020
N	289		289		315		315	315

Robust standard errors in parentheses. The variance is estimated with Hendricks-Koenker method (Koenker 2005) – that is, it assumes independence between the error and independent variables.
*p<0.10, **p<0.05, ***p<0.01 (two-tailed tests)

Discussion

In this study, we propose and empirically test a comprehensive framework to explain drivers of deal popularity in online deal communities, which are a very relevant global phenomenon in today's online markets. We base our analysis on data consisting of 604 smartphones and DVDs & Blu-rays from a major German online deal community, mydealz.de. The results of our analysis provide interesting implications for both researchers and practitioners alike.

First, we contribute to the growing body of literature on human behavior in the context of online deal communities. To the best of our knowledge, this is the first study that investigates the determinants of online deal community members' voting behavior in the user-generated content context. Building on the theory of quality signaling and social influence, we find that characteristics that relate to both intrinsic quality signals (i.e., directly available on a deal's page) and extrinsic quality signals (i.e., obtained from external sources) determine the popularity of online deals.

Along with the expected quadratic (inverted-U) relationship between deal price and deal popularity and the positive effect of discount magnitude on deal popularity, we particularly find evidence for bandwagon effects in online deal communities. More specifically, we find that online deal popularity is largely determined by social cues like comments and opinions spread by other community members. More popular deals attract more attention and receive more votes compared to deals failing to reach the popularity label 'on fire' (i.e, 200 or more hot votes). This leads to self-enhancement. Hence, we are able to extend the findings of, for example, Moe and Schweidel (2012), who find similar effects in the context of product reviews.

Further, our results show that the provision of detailed information on product characteristics and the shipping costs amount in the deal description also significantly contributes to deal popularity. In case of utilitarian products like smartphones, whose quality can be established prior to purchase (Nelson 1974), users especially value deals that feature detailed information on product characteristics. In case of hedonic products like DVDs & Blu-rays, users seem rather to rely on external information cues, such as other users' opinions and experiences, which are usually provided in the form of consumer reviews and ratings.

Online deal community providers can use our results as guidelines for improving the design of their platforms in order to increase the number of (active) community members, the number of deals 'on fire', and consequently the amount of commission earned from posted deals. First, they should stimulate social buzz by encouraging the community members to participate in discussions on current deals. Second, they should encourage deal creators to include more detailed information about the discounted product, reference price as well as amount of shipping costs in the deal description. In case of hedonic products, deal creators should be encouraged to incorporate a product's average quality rating and total number of ratings (e.g., on Amazon). These information cues help to mitigate product uncertainty and better infer a product's fit to the users' preferences. In case of utilitarian products and products associated with high expenses, it would be valuable to provide information on retailer reputation, e.g., in the form of an average reputation rating from a popular price-comparison website.

Based on these results, it is also possible to predict a minimum level of achievable deal popularity which is especially relevant for deals that have been just posted or have so far received very few votes. In other words, given an existing deal, our models and results help to predict a deal's approximate popularity potential based on the proposed framework of influencing factors. This would be an effective way of discovering the deals that would better meet consumer needs and thus increase their satisfaction with the community. Online deal community providers could add an additional 'hotness potential' quality sign, which might capture the community users' interest and, in turn, increase their activity.

Finally, the developed framework is also relevant for manufacturers and retailers as it provides valuable insights into how to design effective price promotions, that is, the characteristics of a deal that are particularly relevant to attract more consumers.

Besides these contributions, however, our results are subject to some limitations. First, our data is limited to two product categories of a single online deal community. Hence, future research could expand the dataset by integrating further product categories and other online deal communities in the analysis. In addition, cross-country data might lead to further insights. Second, our dataset on DVDs & Blu-rays did not contain deals with 'frozen' popularity label (i.e, deals with 200 or more cold votes). However, we would rather perceive this observation as an interesting finding uncovering the differences in voting dynamics across different product categories. Future research should address this issue by investigating this effect on other products, described by hedonic attributes whose quality evaluation is rather subjective. Third, an interesting approach would be to analyze the content of the deal comments to further explore bandwagon dynamics in the community. Nevertheless, our study provides valuable implications for improving the design of online deal communities and opens up interesting venues for the future research.

Appendix A. Correlation Matrix

Table 4. Correlations between Variables

Smartphones		1	2	3	4	5	6	7	8	9	10
1	Deal Price	1.000									
2	Discount Magnitude	0.437	1.000								
3	Number of Comments	0.021	0.249	1.000							
4	Product Description	-0.183	-0.022	0.128	1.000						
5	Shipping Costs Amount	0.050	0.024	-0.073	-0.030	1.000					
6	Deal Scout	-0.179	0.100	0.149	0.267	0.039	1.000				
7	Deal Duration	0.046	0.083	0.082	0.063	0.083	-0.028	1.000			
8	Product Quality Rating	0.094	0.078	0.103	0.040	0.009	-0.097	0.041	1.000		
9	Product Rating Count	0.055	-0.043	0.007	-0.161	-0.125	-0.005	-0.046	0.022	1.000	
10	Retailer Reputation Rating	-0.054	-0.014	-0.003	0.032	-0.118	0.006	0.065	0.050	-0.054	1.000
DVDs & Blu-rays		1	2	3	4	5	6	7	8	9	10
1	Deal Price	1.000									
2	Discount Magnitude	0.449	1.000								
3	Number of Comments	-0.032	0.090	1.000							
4	Product Description	0.006	0.021	-0.109	1.000						
5	Shipping Costs Amount	0.123	0.107	0.051	0.012	1.000					
6	Deal Scout	-0.053	-0.007	-0.142	0.312	-0.007	1.000				
7	Deal Duration	-0.024	-0.013	0.059	0.007	-0.045	-0.142	1.000			
8	Product Quality Rating	0.184	0.143	0.069	0.053	-0.034	0.080	0.009	1.000		
9	Product Rating Count	-0.154	-0.181	0.128	-0.119	-0.038	-0.067	-0.014	-0.213	1.000	
10	Retailer Reputation Rating	-0.003	0.050	-0.019	0.002	-0.043	-0.190	0.094	-0.034	0.028	1.000

Appendix B. Results of Regression for Pooled Data Set

Table 5. Regression Results for Research Model (Pooled Data Set)

	Smartphones + DVDs & Blu-rays			
	Intrinsic Cues		Intrinsic Cues + Extrinsic Cues	
		Std. Coef.		Std. Coef.
Intercept	57.086 (75.491)		41.573 (65.211)	
Deal Price	0.403 (0.254)	0.204	0.313 (0.252)	0.158
Deal Price²	-0.0011*** (0.0004)	-0.301	-0.0011*** (0.0004)	-0.271
Discount Magnitude	1.475*** (0.453)	0.117	1.573*** (0.453)	0.124
Number of Comments	4.853*** (0.211)	0.671	4.788*** (0.211)	0.662
Product Description	21.921 (21.165)	0.031	26.864 (21.224)	0.037
Shipping Costs Amount	-6.157 (5.026)	-0.034	-4.793 (5.027)	-0.027
Deal Scout	102.531*** (19.619)	0.154	104.197*** (19.589)	0.156
Deal Duration	5.750** (2.344)	0.069	5.797** (2.335)	0.069
Product Quality Rating			32.676* (17.519)	0.055
Product Rating Count			0.090*** (0.031)	0.082
Retailer Reputation Rating			8.968 (17.379)	0.014
N	603		603	
Pseudo R^2	0.548		0.557	
AIC	8167.736		8152.601	
BIC	8216.175		8214.252	

Notes: standard errors are listed in parentheses
*p<0.10, **p<0.05, ***p<0.01 (two-tailed test)

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