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# Are all signals equal? Investigating the differential effects of online signals on the sales performance of e-marketplace sellers

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## Abstract

**Purpose** – In the competitive e-marketplace today, sellers are using an increasing number of signals to entice customers to make online purchases. However, how differential these signals are in terms of their capacity to improve sales performance has not yet been investigated. The paper aims to discuss this issue.
**Design/methodology/approach** – Drawing on signaling theory and grounded in the context of China's largest e-marketplace, Taobao, this study investigated the different effects of five commonly used signals on the sales performance of e-marketplace sellers.
**Findings** – The authors find that warranty has the highest effect on sales performance, followed by overall rating, mean detailed seller rating, percent of positives, and web site quality.
**Originality/value** – First, this study builds on signaling theory and contributes to the e-marketplace literature by providing new insights into how specific signals differentially affect sales performance in the e-marketplace (with evidence from a large-scale empirical analysis). Second, the study extends the applicability of signaling theory to the e-marketplace domain by incorporating distinctive features of the e-marketplace into the original signaling theory. Finally, the findings lend practical support to e-marketplace sellers' investment decisions on signals and provide guidelines for deployment of such signals.

**Keywords** Consumer behaviour/choice/demand/empowerment/reviews/consumerism, Customer satisfaction/service, E-commerce (B2B/B2C/B2G/G2C), E-tailing
**Paper type** Research paper

## 1. Introduction

E-marketplaces are online transaction platforms hosted by a third party to facilitate exchanges between sellers and buyers (e.g. Amazon and Taobao). They serve an increasingly important function in e-commerce. For instance, in China in 2013 over

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60 percent of online retailing (worth about 180 billion USD) took place via e-marketplaces (Statistica.com, 2014). The staggering growth of e-marketplaces has been accompanied by intense competition among e-marketplace sellers. For example, more than nine million sellers were competing on Taobao, China's dominant e-marketplace, by the end of 2013. This represents an increase of nearly 50 percent from 2012. While millions of sellers grow their businesses by operating e-marketplace storefronts, potential customers still face the problem of information asymmetry, which deters them from purchasing (Bockstedt and Goh, 2011; Bolton *et al.*, 2008; Ghose, 2009; Mitra and Fay, 2010; Schlosser *et al.*, 2006; Wells *et al.*, 2011). For sellers, the key to e-marketplace success is be better than competitors at addressing such information asymmetry, in order to entice customers to buy.

One common strategy is to give customers extrinsic cues, such as warranties, online reputation indexes, and a visually appealing web site, using functions designed by e-marketplace platform providers. In the signaling literature, these cues would be called "signals" (Spence, 1974). E-commerce scholars generally agree that effective signals can reduce information asymmetry and enhance a customer's trust in transacting with a seller, thereby promoting purchase behavior (Bockstedt and Goh, 2011; Gregg and Walczak, 2008; Kelley, 1988; Lee *et al.*, 2005; Ou and Chan, 2014; Schlosser *et al.*, 2006; Wang *et al.*, 2013). However, little work has been done to rank the effectiveness of these signals in improving sales performance.

Understanding the relative effectiveness of these signals is important from both practical and theoretical perspectives. It is practically important because e-marketplace sellers need to know the relative effectiveness of signals so they can make better signal investment decisions. E-marketplace sellers are unlikely to maximize sales if they only have a general understanding of the positive effect of online signals on performance. Most of these sellers are small or medium sized, so they must direct their limited resources to the signals that work best (Kirmani and Rao, 2000). The current research is also theoretically important because, as the general e-commerce literature shows, signals can increase customer purchase intentions (Bockstedt and Goh, 2011; Gregg and Walczak, 2008; Kelley, 1988; Lee *et al.*, 2005; Schlosser *et al.*, 2006; Wang *et al.*, 2013); however, little effort has been made to compare the effects of such signals, particularly in the e-marketplace. As we will discuss later, the e-marketplace has certain functions that support sellers to display signals to customers. These functions might impact the relative effectiveness of signals in context-specific ways. Thus, this research develops nuanced insights into how signaling theory can be used to explain the comparative effects of different signals in the e-marketplace context, as advocated in recent research (Srivastava and Lurie, 2004). To this end, this study aims to examine a research question on which the literature is resoundingly silent: "What are the differential effects of signals on the actual sales performance of e-marketplace sellers?"

To address this research question, we review the existing literature and conduct an extensive survey of the major e-marketplaces to indentify the five signaling functions most commonly used by e-marketplace sellers. These are: warranty, overall rating, percent of positives, mean detailed seller rating (DSR), and web site quality. It is noteworthy that, although the literature sometimes defines price-related information as a signal (Biswas and Biswas, 2004; Dutta and Bhowmick, 2009; Li and Hitt, 2010; Mitra and Fay, 2010; Srivastava and Lurie, 2004), most e-marketplace sellers are reluctant to compete solely on price. This is because competing via price signals quickly escalates into a "price war" which eventually surrenders the overall benefit of the supply side of the e-marketplace (i.e. sellers) to the demand side

(i.e. customers). Therefore, the present study focusses on the aforementioned five non-price-related signals. We then extend signaling theory to develop a research model that compares the effects of these different signals. The model highlights the key function that signaling cost plays in determining the effect of a signal. The model is contextualized to the distinctive e-marketplace milieu context, in which we believe several e-marketplace platform features play a role in changing signaling costs. We test our research hypotheses through 15,890 seller-month observations on Taobao.com, the largest e-marketplace in China.

This study makes several theoretical and practical contributions. First, it builds on signaling theory and contributes to the e-marketplace literature by providing new insights into how specific signals differentially affect sales performance in the e-marketplace (with evidence from a large-scale empirical analysis). Second, the study extends the applicability of signaling theory to the e-marketplace domain by incorporating distinctive features of the e-marketplace into the original theory. Finally, the findings lend practical support to e-marketplace sellers' signal investment decisions and provide guidelines for deploying such signals.

The remainder of this paper is structured as follows: first, we introduce signaling theory, then describe the role of signals in the e-marketplace and consumers' perceived signal costs, which determine the effectiveness of signals. Second, we develop hypotheses on the relative effectiveness of five types of signal instruments in improving sales performance. Third, we report empirical examinations using a data set of 15,890 seller-month observations over ten months. Finally, we discuss the implications and limitations of the study and future research directions.

## 2. Theoretical foundation

### *2.1 Signaling theory*

Signaling theory emerged from information economics studies, under conditions in which the two parties of an exchange (e.g. sellers and buyers, IPO firms and investors, employee and employer) face asymmetric information in their interactions (Spence, 1974). This theory has been extensively studied in management (Connelly *et al.*, 2011), marketing (Kirmani and Rao, 2000), and finance (Cooper and Kagel, 2005). It provides a framework for understanding how signalers (e.g. sellers) can use extrinsic cues to convey product and service quality information to receivers (e.g. buyers) to reduce their perceived uncertainty and facilitate exchange in an environment characterized by high-information asymmetry (Wells *et al.*, 2011). In the traditional offline environment, the cue may be the brand (Rao *et al.*, 1999), reputation (Chu and Chu, 1994; Dawar and Parker, 1994), price (Anderson and Simester, 2001; Simester, 1995), warranties (Balachander, 2001; Boulding and Kirmani, 1993; Kelley, 1988; Wiener, 1985), or store environment (Baker *et al.*, 1994; Bloom and Reve, 1990).

### *2.2 The role of signals in the e-marketplace*

In the e-commerce literature, a signal is defined as "a cue that a seller can use to convey information credibly about unobservable product quality to the buyer" (Wells *et al.*, 2011, p. 375). Signals serve an important function in reducing the information gap in the e-marketplace, where spatial and temporal gaps amplify information asymmetry between buyers and sellers (Wells *et al.*, 2011). Major e-marketplaces commonly use three categories of signals: warranties, reputations, and web site quality. Table I summarizes the signals used in the major e-marketplaces.

| E-marketplace | Alexa traffic rank: Rank in country | Alexa traffic rank: Global rank | Signals: Warranties | Signals: Reputations: Overall rating | Signals: Reputations: Percent of positives | Signals: Reputations: Detailed seller rating | Signals: Web site quality |
|---|---|---|---|---|---|---|---|
| Amazon.com | USA: 5 | 7 | ✓ | ✓ | | | |
| Taobao.com | CN: 3 | 13 | ✓ | ✓ | ✓ | ✓ | ✓ |
| eBay.com | USA: 9 | 21 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Etsy.com | USA: 43 | 159 | ✓ | ✓ | | | |
| Overstock.com | USA: 242 | 899 | ✓ | ✓ | | | ✓ |
| Wanggou.com | CN: 114 | 1,034 | ✓ | | ✓ | ✓ | ✓ |
| Souq.com | SA: 31 | 1,182 | ✓ | | ✓ | | ✓ |
| Trademe.co.nz | NZ: 5 | 1,810 | | ✓ | ✓ | | |

**Note:** ✓, the signal is used by sellers in this e-marketplace

**Table I.** Summary of signals in the major e-marketplaces

Unlike the offline environment, an e-marketplace platform provider helps its sellers deploy these three signals. First, the e-marketplace provides third-party assurance for a seller's warranty by collecting deposits from sellers. The seller is required to pre-pay a deposit to establish a warranty policy and promote it to potential customers. If a product fails, the e-marketplace draws on the deposit to immediately compensate the consumer, then bills the seller for any difference. Second, the e-marketplace platform provider equips sellers with the tools to collect and aggregate customer feedback (e.g. overall rating, percent of positives, DSR, as discussed below). Third, the e-marketplace platform provider also provides web site templates to help sellers develop their infrastructure and web storefronts. For example, Taobao offers the "luxurious storefront" template, which can be used to build professional-looking web sites and visually impressive storefronts.

The next section considers the mechanisms through which these signals affect sales performance and the open questions in the literature.

*2.2.1 Warranty*. Spence (1974) introduced the signaling role of warranties, which are a form of insurance against product failure. Following Spence's pioneering work, a substantial body of research has examined how warranties serve as a quality signal (Balachander, 2001; Boulding and Kirmani, 1993; Kelley, 1988; Ou and Chan, 2014; Soberman, 2003; Wiener, 1985), particularly in the e-marketplace where information asymmetry is high. Warranties represent a strategic marketing decision point for sellers because they are costly to provide (Balachander, 2001), but perceived by consumers as a signal of product reliability and a form of protection (Kelley, 1988).

High-quality sellers attract more consumers by offering insurance against product failure and so expect increased returns from repeat buying (Heal, 1977). By contrast, low-quality sellers do not provide warranties, because a default contingency and false signal may damage their reputation and hurt their sales performance. Overall, consumers generally prefer a seller who offers warranties over one who does not. In other words, warranties provide a "separating equilibrium" that enables consumers to distinguish among sellers (Boulding and Kirmani, 1993). Thus, e-marketplace seller warranties are positively associated with sales performance.

*2.2.2 Reputation*. Reputation is generally defined as "a perception of a seller's past actions and future prospects" (Bockstedt and Goh, 2011, p. 237); it is one of the most studied signals of product quality and risk reduction (Biswas and Biswas, 2004). Reputation is typically measured based on feedback ratings by past buyers; and these ratings provide signals that reduce information asymmetry and build buyers' trust in sellers (Bockstedt and Goh, 2011; Dellarocas, 2003; Gregg and Scott, 2006; Pavlou and Gefen, 2004). Existing empirical research on the traditional offline environment confirms the positive relationship between firm reputation and performance (Brown and Perry, 1994; Connelly *et al.*, 2011; Deephouse, 2000; Fombrun and Shanley, 1990; Fryxell and Jia, 1994; Roberts and Dowling, 2002; Soberman, 2003). Reputation plays an even more important role in predicting the sales performance of e-marketplace sellers (Bockstedt and Goh, 2011; Pavlou and Dimoka, 2006) because gaps in time and space make the e-marketplace environment more uncertain than the traditional offline environment (Bockstedt and Goh, 2011; Pavlou and Dimoka, 2006).

In recent years, mechanisms have been established to help e-marketplaces succeed and prevent the emergence of a market of lemons. For example, transaction platform providers offer various reputation indexes to differentiate among sellers and enhance their sales performance (Bockstedt and Goh, 2011; Cabral and Hortaçsu, 2006; Ou and Chan, 2014; Pavlou and Dimoka, 2006). For instance, Cabral and Hortaçsu (2006) identified two eBay reputation indexes: overall rating and percent of positives. In their study, overall rating refers to the sum of scores received by a seller (Cabral and Hortaçsu, 2006). It is one of the most important aspects of feedback profile and is usually displayed in parentheses next to the seller's eBay ID. The percent of positives is the percentage of positive ratings given by buyers in the last 12 months and is calculated by dividing the number of positive ratings by the total number of ratings (Cabral and Hortaçsu, 2006). eBay adds other detailed ratings of product quality, distribution, and service (e.g. DSRs) to seller feedback profiles to help consumers choose among sellers (Wang *et al.*, 2013). Since Cabral and Hortaçsu (2006) study, a considerable amount of research has gone into designing reputation mechanisms (Clemons, 2007; Dellarocas, 2005, 2006; Li, 2010; Zhang, 2006). However, few of these designs compare the effects of different aggregates of seller feedback. Such a comparison could provide deep insights into how sellers may invest in and improve their reputation; hence, this study takes the first step to examine the effectiveness of each reputation index, in isolation.

*2.2.3 Web site quality*. As the only point of contact for most e-businesses, a seller's store web site plays an important role in conveying information about the store and its products and services (Gregg and Walczak, 2008). When a customer shops in a physical store, the store environment provides informational cues about merchandise and service quality (Baker *et al.*, 1994). The quality of an e-marketplace seller's web site similarly serves as a conditioning factor for customers' trusting beliefs and purchase intentions (Kim and Niehm, 2009; Mitra and Fay, 2010).

The dimensions of web site quality considered in prior studies include visual appeal, data quality, and security. Visual appeal refers to the esthetics of a web site (Loiacono *et al.*, 2002); a visually pleasing design (e.g. a luxurious storefront) helps form a good impression that affects the consumer's willingness to buy (Loiacono *et al.*, 2002). Data quality denotes the extent to which the information displayed is accurate and comprehensible (Aladwani and Palvia, 2002; Barnes and Vidgen, 2001; Ranganathan and Ganapathy, 2002). For example, a comprehensive description of a product or

service reduces consumers' perceived uncertainty about product quality and thus influences their purchasing decisions. Security indicates whether or not customers feel that their financial information is kept private and secure during an internet business transaction (Liu and Arnett, 2000; Ranganathan and Ganapathy, 2002; Webb and Webb, 2004). The current study focusses only on the visual appeal and data quality of the e-marketplace because sellers using the same e-marketplace platform all offer the same level of security.

Table II summarizes the extant literature on e-commerce signaling. Most early signaling studies examine how each of these signals influences consumers' perceptions of product quality (Biswas *et al.*, 2009; Gregg and Walczak, 2008), risks (Alicia and Esther, 2011; Biswas and Biswas, 2004), trust (Alicia and Esther, 2011; Arnold *et al.*, 2007; Bolton *et al.*, 2008; Lee *et al.*, 2005; Wang *et al.*, 2004), and purchase intention (Gregg and Walczak, 2008; Wells *et al.*, 2011). Only a few recent studies have considered the effect of signals on sellers' actual sales performance (Amblee and Bui, 2011; Bockstedt and Goh, 2011; Li *et al.*, 2009; Ou and Chan, 2014). For instance, Li *et al.* (2009) investigated how sellers can use different online auction features as quality signals to alleviate buyer uncertainty and thus impact eBay auction outcomes. Similarly, Bockstedt and Goh (2011) examined the contingent role of competition concentration in eBay sellers' choice between visibility-enhancing and signaling-quality strategies. Amblee and Bui (2011) studied the signal role of electronic word-of-mouth in improving the sales of digital microproducts on Amazon. Ou and Chan (2014) distinguished two different signaling mechanisms in influencing sales performance and found that that product type had a moderator role in these two mechanisms on Taobao. Nevertheless, no prior work has theoretically and empirically compared the relative effectiveness of each signal in enhancing sales performance.

### *2.3 Signal cost*

The extant literature on signaling suggests that signal cost serves an important function in determining the effectiveness of signals (Busenitz *et al.*, 2005; Cohen and Dean, 2005; Connelly *et al.*, 2011; Goranova *et al.*, 2007; Lee, 2001; McGrath and Nerkar, 2004; Srivastava, 2001). Signal costs refers to the transaction costs associated with implementing a signal, as evaluated by signal receivers. Signals that are more credible or valid are the ones that signal receivers (e.g. consumers (Srivastava, 2001), investors (Busenitz *et al.*, 2005), and competitors (McGrath and Nerkar, 2004)) perceive as more costly to implement than others. For instance, in a given exchange scenario, consumers who are unsure about intrinsic product quality will usually turn to extrinsic cues, such as warranties or reputations (i.e. signals). However, customers do not treat all these signals equally, given that they are more likely to attend to costly signals than to other signals (Busenitz *et al.*, 2005; Cohen and Dean, 2005; Lee, 2001; McGrath and Nerkar, 2004; Srivastava, 2001). The cost here refers to consumers' perceptions of either the potential expenditure of up-front investments in these signals (e.g. monetary expenditures on the design of store web site) or the occurrence of a future expenditure (e.g. monetary compensation for product failure via warranty).

Signal cost is extremely important to signaling theory to the extent that some scholars refer to the theory as the "theory of costly signaling" (Connelly *et al.*, 2011, p. 45). The superior status of a signal cost in the signaling process arises from the basic requirement for a signal to generate a "separating equilibrium" that allows consumers to distinguish between high-quality and low-quality sellers (Kirmani and Rao, 2000).

| Signal | Signal outcomes | Findings | References |
|---|---|---|---|
| Warranty – retailer assurance | Trust | The timing of assurances is an important aspect of personalizing the online retail experience | Arnold *et al.* (2007) |
| Warranty – return policy | Trust, bookmarking intentions, and willingness to provide personal information | The results supported most of signaling roles of these cues | Wang *et al.* (2004) |
| Warranty – money-back guarantee | Trust | Trust is developed through signals that are sent and received between the two sides of a potential transaction | Lee *et al.* (2005) |
| Warranty – return policy, customer protection scheme; reputation | Sales performance | Newcomers can use social-based quality singling mechanisms (e.g. virtual presence, product, and shop tagging) to enter the market, while core players can use such signals to strengthen their market leadership | Ou and Chan (2014) |
| Warranty – money-back guarantee; reputation | Auction outcomes | Directly revealing information on product quality and seller credibility encourages bidders to participate in or shade bids | Li *et al.* (2009) |
| Warranty – return policy; reputation | Product quality | A signal's stand-alone credibility largely determines whether or not its individual strength is diluted or augmented by the coexistence of another signal | Biswas *et al.* (2009) |
| Warranty reputation | Perceived risks | Signals function as stronger risk reducers online than in-store shopping, particularly for products with many non-digital attributes | Biswas and Biswas (2004) |
| Reputation | Auction outcomes | Auction outcomes are affected by the use of auction attributes that can signal quality | Bockstedt and Goh (2011) |
| Reputation | Trust | Encouraging competition improves the effectiveness of feedback systems in internet markets | Bolton *et al.* (2008) |
| Reputation | Sale time | High-quality goods take a longer time to sell than low-quality goods; this tenet holds when we examine the relationship between the reputation scores of sellers and the time they take to sell | Ghose (2009) |
| Reputation – eWOM | Sales performance | eWOM can be used to convey the reputation of the product, brand, and complementary goods | Amblee and Bui (2011) |
| Reputation – eWOM | Trust and perceived risk | Quality signals indirectly influence customers' intentions to reserve a hotel room over the internet, because such signals mitigate information asymmetries, thereby | Alicia and Esther (2011) |

(*continued*)

**Table II.**
Summary of extant literature on e-commerce signaling

| Signal | Signal outcomes | Findings | References |
|---|---|---|---|
| | | decreasing risk and increasing trust | |
| Web site quality | Purchase intention | Highly impulsive consumers can be both positively and negatively influenced by various degrees of web site quality | Wells *et al.* (2011) |
| Web site quality | Product or company quality, purchase intention, and transaction price | Increasing the e-image quality of an auction business increases the willingness of consumers to transact businesses and prices | Gregg and Walczak (2008) |
| Others – web site signals | Trust and purchase intention | The absence of web site trust signals creates the perception that a seller is untruthful and decreases consumers' willingness to buy online | Mavlanova and Benbunan-Fich (2010) |
| Others – web site design investments | Trust and purchase intention | Web site design investments can signal trustworthiness, which is strongly related to online purchase intentions | Schlosser *et al.* (2006) |
| Others – web site provides recommendations and consumer reviews | Perceived usefulness and social presence of the web site | Providing recommendations and consumer reviews enhances the perceived usefulness and social presence of the web site | Kumar and Benbasat (2006) |
| Others – third-party certification, objective-source rating, etc. | Trust | Third-party certification has the greatest effect on perceived trustworthiness, which in turn influences the respondents' willingness to divulge personal information | Aiken and Boush (2006) |
| Others – third-party assurance seals | Trust | Given that third-party assurance seals are neither noticed on merchant web sites nor adequately understood by consumers, they may not fulfill their potential to influence consumer trust in e-commerce | Kimery and McCord (2006) |
| Others – joining seal-of-approval programs, privacy policy | Trust | The extent to which retailers influence consumer trust crucially depends on the clarity and credibility of the signals they send | Tang *et al.* (2008) |
| Others – trust mark program subscription | Transaction price | A trust mark program subscription can signal the relatively better type of sellers and increase their transaction price | Zhao *et al.* (2006) |

**Table II.**

That is, the signal cost helps consumers infer the intrinsic product and service quality by generating two conditions: first, for high-quality sellers, the gains from signaling outweigh the gains from non-signaling; and second, for low-quality sellers, the larger payoff is provided by adopting a non-signaling strategy. However, consumers may be vulnerable to the seller who signals high quality without the concomitant guarantee of quality, a problem commonly known as "adverse selection" (Ghose, 2009; Li *et al.*, 2009;

Mavlanova *et al.*, 2012). To overcome this problem, consumers tend to attribute higher credibility to signals with higher signal cost, because a failure would be very costly for this seller (Kirmani and Rao, 2000). Thus, a higher signal cost indicates greater signal effectiveness (Busenitz *et al.*, 2005; Cohen and Dean, 2005; Lee, 2001; McGrath and Nerkar, 2004; Srivastava, 2001).

The following section theorizes and proposes hypotheses on the differential effects of the five most notable signals – warranty, overall rating, percent of positives, mean DSR, and web site quality – on the actual sales performance of e-marketplace sellers.

## 3. Hypotheses development

Signals can be an important way for sellers to convince consumers of their product quality and persuade them to buy; however, prior studies have suggested that their effects may vary significantly, depending on consumer perceptions of signal cost (Srivastava, 2001). In the e-marketplace, buyers infer the quality of a product based on their perception of the cost of the signal to the seller. Accordingly, we examine the signal cost, as perceived by buyers, of each of the aforementioned five signals, and theorize their relative effects on the actual sales performance of sellers.

Figure 1 takes three steps to compare the effects of the signals used by e-marketplace sellers on actual sales performance. First, we compare the effects of warranty vs reputations and web site quality. Second, we individually compare the effects of the three reputation indexes. Third, we compare the effects of three reputation indexes on sales performance, with that of web site quality. In particular, we situate our hypotheses development in the context of China's largest e-marketplace, where seller signals are commonplace.

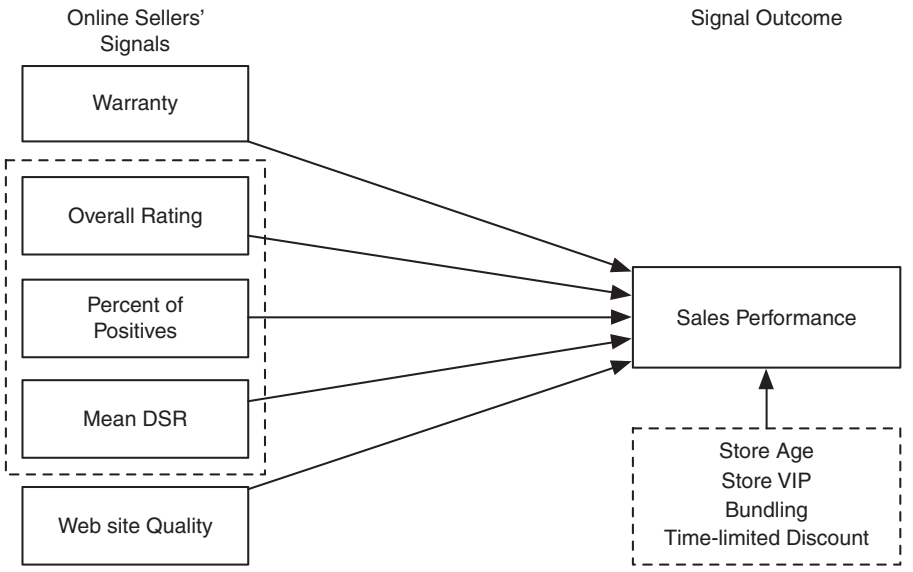



**Figure 1.**
Research model

*3.1 Warranty vs reputations and web site quality*

We argue that warranty has a stronger positive effect on e-marketplace sales performance than reputation and web site quality, for two reasons. First, in an exchange between two parties (i.e. seller and consumer), the monetary expenditure of one party (seller) is essentially transmitted as the utility of the other party (consumer) and vice versa (Kirmani and Rao, 2000). Thus, the utility that the consumer receives partially reflects the seller's cost. A consumer is more sensitive to costs associated with a transaction from which they derive vital benefits (i.e. warranty, such as triple compensation for fake products) than to a transaction cost that does not (i.e. reputation and web site quality) (Kirmani and Rao, 2000). Second, a well-known e-marketplace policy (e.g. Taobao) is that sellers offering warranties must give monetary escrow deposits to platform operators, regardless of whether they default on his/her claims. This policy allows the platform operator to serve as a monitor during the signaling process through strong disciplinary mechanisms. This policy deters low-quality e-marketplace sellers from conducting "adverse selection," a problem often observed in traditional (offline) markets, because deposits are paid upfront (Kirmani and Rao, 2000; Rao *et al.*, 1999). One of the most widely used warranties on Taobao is a guarantee of triple compensation for fake products. Sellers have to pay deposits to subscribe to this service if they want to promote the warranty on their web sites. Platform operators then use these deposits to compensate consumers if sellers refuse to address product failure (Taobao.com). In contrast with warranty, reputations and web site quality are perceived as relatively low-cost signals because sellers deliberately declare monetary expenditures for consumers when sending out these signals. Hence, we hypothesize that:

*H1-H4.* Compared with warranty, the three reputation indexes (i.e. overall rating (*H1*), percent of positives (*H2*), and mean DSR (*H3*)) and web site quality (*H4*) have a weaker effect on e-marketplace sales performance.

*3.2 Overall rating, percent of positives, vs mean DSR*

E-marketplace seller web sites (e.g. Taobao) often display three reputation indexes: overall rating, percent of positives, and mean DSR. Consumers have different perceptions about the costs of these three reputation indexes. Specifically, we argue that consumers perceive the cost of overall rating (i.e. sum of scores a seller receives) to be higher than that of percent of positives (i.e. percentage of positive ratings from total ratings). The difference between the overall rating cost and percent of positives cost (i.e. accumulative value vs fractional value) leads the consumer to recognize that the latter depends less on the number of transactions and easily reaches a higher value than the former. For example, a seller with a low-overall rating can have a high percent of positives by only engaging in a few transactions. This observation is particularly true for sellers who are just starting their businesses and have few customers; it is relatively easy for these sellers to have a high percent of positives. However, this observation does not imply that start-up sellers are more credible than established sellers (who have a better overall rating).

We also argue that consumers perceive mean DSR (i.e. DSRs about product quality, distribution, or service) to be less costly than percent of positives. This situation arises because consumers may notice an apparent improvement in mean DSR when the seller invests in a single weak dimension; whereas they would not notice an improvement in

percent of positives unless the seller invests in all dimensions. For example, the mean DSR of a seller with a low-quality product and an ineffective distribution system can be improved by investing in either of these dimensions. But the percent of positives will remain the same, because it represents the consumer's overall assessment of the seller which is influenced by inadequacy in even a single dimension. Thus, we hypothesize that:

*H5.* The overall rating of an e-marketplace seller is more strongly associated with sales performance than mean DSR.

*H6.* The overall rating of an e-marketplace seller is more strongly associated with sales performance than percent of positives.

*H7.* The percent of positives of an e-marketplace seller is more strongly associated with sales performance than mean DSR.

### *3.3 Reputations vs web site quality*

We further argue that consumers believe it is less expensive to achieve high web site quality compared to the three reputation indexes, because sellers must satisfy past consumers. The reasons for this are twofold. First, platform providers provide e-marketplace sellers with web sites that are usually based on templates; recent consumer personalization experiences of popular personal web sites embedded in online social network platforms have revealed some of the secrets of template-based sites. Consumers mistakenly believe that it is relatively inexpensive and easy for online sellers to create a high-quality web site hosted in an e-marketplace, even though building and maintaining an independent professional business web site is costly (Allbusiness.com). Second, unlike investments in reputation, which need to be endorsed by previous consumers, sellers have better control over web site development by subscribing to template-based sites and spending time to maintain their web site. Therefore, we argue that consumers may well recognize that it is easier for sellers to enhance their web site quality than improve their reputation. Overall, consumers perceive investments in web site quality as less costly than investments in reputation. Hence, we deduce that the rank order (from highest to lowest) of the signal effects on sales performance is overall rating, percent of positives, mean DSR, and web site quality. Thus, we hypothesize that:

*H8-H10.* The overall rating (*H8*), percent of positives (*H9*), and mean DSR (*H10*) of an e-marketplace seller are more strongly associated with sales performance than web site quality.

## 4. Research methodology

This section describes our sampling method, operationalization of model variables, and data analysis results.

### *4.1 Sample*

Taobao is the biggest online consumer-to-consumer e-marketplace in China and Asia. It connects more than 900 million registered users and has nearly 800 million product lines that range from food and clothing to high-tech products. We grounded our study in the context of Taobao because, as a hypercompetitive environment, it is inundated with signals meant to distinguish sellers from one another; the diversity of these signals makes it an appropriate context to test the research model proposed in this study.

To test the hypotheses developed, we randomly selected 1,589 Taobao sellers in the apparel industry and observed their use of these signals and their sales performance for a period of ten months. The apparel industry well satisfies the condition for a signal to work, because clothing is a typical-experience product: it is difficult to evaluate prior to purchase but easy to evaluate once in the consumers' hands (Wells *et al.*, 2011). Observations at the end of each month were collected and used in data analysis.

### *4.2 Measurement*

*4.2.1 Dependent variables*. Sales performance is the dependent variable of our model. The most widely used measures for sales performance in the e-commerce literature are product-specific sales rank and sales volume (i.e. amount of transactions). The present study uses seller-specific average daily revenue over the past one month to capture sales performance, because our signals of interest are all seller specific rather than product specific. In addition, we use the logarithm of average daily revenue in the regression because it exponentially increases over time.

*4.2.2 Independent variables*. There are five independent variables of interest in this study: warranty, the three reputation indexes (i.e. overall rating, percent of positives, mean DSR), and web site quality.

First, we found that Taobao sellers provided three types of warranty: first, triple compensation for fake products, whereby consumers receive three times indemnity for fake goods; second, money-back guarantee within seven days, whereby consumers can return and exchange goods without reason within seven days after purchase; and third, an unequivocal consumer protection service agreement, whereby sellers comply with certain agreed obligations. We used the number of warranties activated by a seller over the past one month as the indicator of warranties.

Second, reputation has three indexes, which are displayed on the seller's web site: overall rating, percent of positives, and mean DSR. The overall rating, also known as Taobao "star rating" captures the sum of positives minus negatives provided by past consumers (Cabral and Hortaçsu, 2006). The percent of positives represents the percentage of positive ratings among the total number of ratings (Cabral and Hortaçsu, 2006). The mean DSR denotes the average values of the three types of DSR (i.e. product quality, distribution, and service DSR) (Wang *et al.*, 2013).

Third, web site quality was measured based on visual appeal and information quality (Aladwani and Palvia, 2002; Loiacono *et al.*, 2002). We used luxurious store web site status (i.e. a certain type of Taobao template-based site) and detailed pictures as proxies for the two dimensions. We summed these two values to reflect the quality of the web site as a whole. Table III summarizes the measurements of variables in the empirical analysis.

*4.2.3 Control variables*. To better test our hypotheses, we set several theoretically salient control variables to isolate their effects on the variables of interest. The controls were: first, store age (Baum and Korn, 1999), which is the number of months since a seller opened a Taobao store; and second, pricing action (Chi *et al.*, 2010), which refers to discounts and sales incentives, such as store VIPs (selected customers receive special store privileges), bundling (price reductions or discounts when purchasing a combination of goods), and time-limited discounts (price reductions within extremely short periods).

Table IV reports the descriptive statistics of all variables. The average store age is 30.6 months. The mean values of warranty and web site quality (i.e. 1.280 and 0.754)

| Variable | Measurement |
|---|---|
| Sales performance | The logarithm of average daily revenue over past one month |
| Warranty | Enrollment status of three types of warranty over the past one month: first, triple compensation for fake products; second, money-back guarantee within seven days; and third, consumer protection service. Scale: 0-3 |
| Overall rating | The total feedback score (i.e. the difference between positives and negatives) received by a seller from consumers at the end of last month. Scale: 1, 2, 3, etc. |
| Percent of positives | The percentage of positive feedback over total feedback at the end of last month |
| Mean DSR | The average value of three detailed seller ratings with regard to product quality, distribution, and service at the end of last month |
| Web site quality | Deployment status of the following two features over the past one month: luxurious store web site; and detailed pictures. Scale: 0-2 |

**Note:** In the empirical analysis, the numerical value of overall rating is normalized via a function defined by the transaction platform as shown the web site: http://service.taobao.com/support/seller/knowledge-847753.htm

**Table III.** Measurements of variables in the empirical analysis



denote that a seller deploys at least one warranty on average, and offers at least one service from luxurious store web site and detailed pictures. The average values of the three reputation indexes for overall rating (scale: natural number), percent of positives (scale: 0-1), and mean DSR (scale: 0-5) are 25,997.080, 0.997, and 4.731, respectively. Table IV also shows that the highest correlation among all variables (i.e. 0.378) is below the criterion value (i.e. 0.7) (Gnyawali *et al.*, 2010). The highest variance inflation factor is below 3, which suggests that multicollinearity is not a major concern for our study.

### *4.3 Data analysis*

To compare the relative effectiveness of the five signal instruments in improving the sales performance of e-marketplace sellers, we used three methods to ensure the robustness of the findings: partial least square (PLS) and ordinary least squares (OLS) regression based on one cross-section data of 1,589 sellers; and fixed-effects model based on the longitudinal data of 15,890 observations over ten months. We first conducted PLS regression and statistically compared the path coefficients following the steps suggested by Chin (2003) and Pavlou and Dimoka (2006). We then conducted robust test in two ways: first, using the OLS regression to test the research and comparing the $R^2$ change by excluding each signal from the full model; and second, using seller fixed-effects model to account for possible endogeneity issues along with some unobservable seller-specific factors and comparing the $R^2$ change when alternatively excluding one signal from the full model.

*4.3.1 PLS regression based on cross-section data.* Following the two steps suggested by Chin (2003) and Pavlou and Dimoka (2006), based on the cross-section data at $T1$, we first tested the relationship between the five signal instruments and sales performance using PLS regression, and obtained the respective path coefficient ($\beta$) and standard error (SE) for each instrument. We then tested the pairwise statistical difference among path coefficients of the five signal instruments using Chin (2003) equation – $t = (\beta_1 - \beta_2)/((\mathrm{SE}_1^2 + \mathrm{SE}_2^2)/N)^{0.5}$, where $t$ refers to the $t$-value, $\beta_1$ and $\beta_2$ denote the two path coefficients under comparison, $\mathrm{SE}_1$ and $\mathrm{SE}_2$ refer to the SE of each path, and $N$ refers to the sample size – which is an adaptation of the traditional $t$-test.

**Table IV.**
Descriptive statistics and correlations of all variables

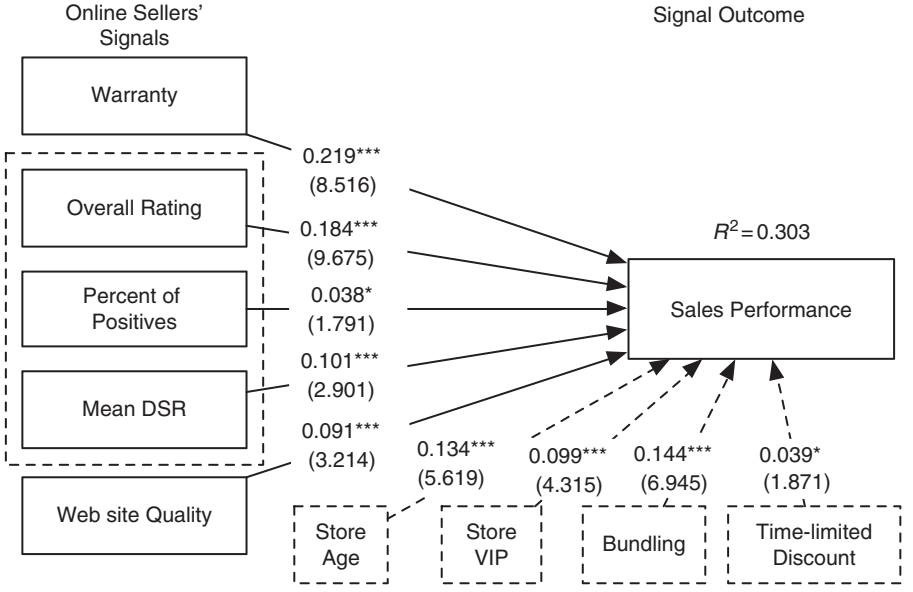
| Variables | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Sales performance | 1,938.516 | 7,729.699 | 1 | | | | | | | | | |
| 2. Store age | 30.644 | 19.721 | 0.300** | 1 | | | | | | | | |
| 3. Store VIP | 0.226 | 0.418 | 0.334** | 0.373** | 1 | | | | | | | |
| 4. Bundling | 0.228 | 0.420 | 0.330** | 0.212** | 0.378** | 1 | | | | | | |
| 5. Time-limited discount | 0.049 | 0.216 | 0.143** | 0.093** | 0.124** | 0.167** | 1 | | | | | |
| 6. Warranty | 1.280 | 0.885 | 0.357** | 0.194** | 0.285** | 0.325** | 0.093** | 1 | | | | |
| 7. Overall rating | 25,997.080 | 173,986.284 | 0.304** | 0.244** | 0.215** | 0.171** | 0.168** | 0.119** | 1 | | | |
| 8. Percent of positives | 0.997 | 0.006 | 0.008 | −0.053** | 0.006 | −0.001 | −0.020* | −0.106** | 0.007 | 1 | | |
| 9. Mean DSR | 4.731 | 0.753 | 0.157** | −0.018* | 0.040** | 0.060** | 0.032** | 0.012 | 0.091** | 0.063** | 1 | |
| 10. Web site quality | 0.754 | 0.433 | 0.023** | −0.104** | 0.003 | 0.030** | 0.000 | −0.028** | −0.074** | 0.025** | 0.092** | 1 |

**Notes:** Store VIP, bundling, and time-limited discount are all binary variables, which indicates whether the seller uses the feature or not in the past one month with 1 for "yes" and 0 for "no". *,**Correlation is significant at 0.05 and 0.01 levels, respectively (two-tailed)

Figure 2 shows the PLS regression results using SmartPLS (Ringle *et al.*, 2005). The $R^2$ value of the dependent variable is 0.303, which implies that 30.3 percent of the variation of sales performance is predicted by all the independent and control variables. The path coefficients of the five signal instruments (e.g. warranty, overall rating, percent of positives, mean DSR, and web site quality) are 0.219, 0.184, 0.038, 0.101, and 0.091. All five signal instruments significantly affect sales performance, although the effect of percent of positives is rather weak ($\beta = 0.038$, $t = 1.791$). It can be preliminarily ascertained that: the effectiveness of warranty in improving sales performance is the highest among the five signals, and overall rating comes second, followed by mean DSR, web site quality, and percent of positives.

To statistically evaluate and compare their effects, we used Chin's (2003) equation and developed a path coefficient comparison table based on the path coefficients and SEs obtained in the first step (see Table V). The value outside the parentheses is $\Delta\beta$, which denotes the difference between the $\beta_1$ that belongs to the row signal instrument and the $\beta_2$ that belongs to the column signal instrument. The values enclosed in parentheses are *t*-values, which are obtained by using the aforementioned equation $t = (\beta_1 - \beta_2)/((SE_1^2 + SE_2^2)/N)^{0.5}$. The results indicate that all the pairwise differences among the five path coefficients are significant, suggesting that the five signals have significantly different effects on sales performance. All hypotheses are supported, except for the two pairs of comparison: percent of positives vs mean DSR (*H7*) and percent of positives vs web site quality (*H9*).

*4.3.2 Robust test*. We then conducted step-wise OLS regressions to obtain the $R^2$ change when excluding each signal instrument from the full model. Table VI presents the results for all the standardized variables in the seven models. Model 1 includes the control variables only and shows that, as expected, store age, store VIP, bundling, and




**Notes:** *$p<0.1$; **$p<0.05$; ***$p<0.01$

**Figure 2.**
Path coefficients using PLS regression

| Variable | $\beta$ | SE | Web site quality | Mean DSR | Percent of positives | Overall rating | Warranty |
|---|---|---|---|---|---|---|---|
| Web site quality | 0.091 | 0.025 | – | | | | |
| Mean DSR | 0.101 | 0.035 | *H8*: supported 0.009*** (8.674) | – | | | |
| Percent of positives | 0.038 | 0.021 | *H9*: not supported −0.053*** (−65.365) | *H7*: not supported −0.063*** (−61.267) | – | | |
| Overall rating | 0.184 | 0.020 | *H10*: supported 0.093*** (115.546) | *H5*: supported 0.084*** (82.370) | *H6*: supported 0.146*** (202.987) | – | |
| Warranty | 0.219 | 0.024 | *H4*: supported 0.128*** (146.320) | *H3*: supported 0.119*** (110.711) | *H2*: supported 0.181*** (227.182) | *H1*: supported 0.035*** (44.428) | – |

**Table V.**
Hypotheses testing results based on the path coefficients of PLS regression

**Notes:** $n = 1{,}589$. The values outside the parentheses are the differences of two corresponding $\beta$-values, while values enclosed inside the parentheses are $t$-values. *$p < 0.1$; **$p < 0.01$; ***$p < 0.001$

time-limited discount significantly affect sales performance. Model 7 is the full model that includes all the variables. Each of Models 2-6 exclude only one independent variable (i.e. one of the five signal instruments) from the full model. As shown in Table VI, all five signal instruments significantly affect sales performance. Next, we calculated the differences among the $R^2$ of these models, which indicates the different effectiveness of each of the signal instruments. Specifically, after excluding the corresponding independent variable from the full model, the ranking (highest to lowest) of the decrease of $R^2$ of these models is as follows: Model 2 warranty (0.0330); Model 3 overall rating (0.0325); Model 5 mean DSR (0.0099); Model 6 web site quality (0.0054); and Model 4 percent of positives (0.0013).

As some unobservable seller-specific factors may confound the results, we applied fixed- or random-effects models to account for the possible endogeneity issues (Wooldridge, 2002) and to further test the robustness of our results. We performed Hausman test to select between fixed- or random-effects models. The result was significant, indicating that the estimates of the fixed-effects model are more efficient than those of the random-effects model. Table VII shows the results for all seven models that are parallel to those in Table VI. The dependent variable is the logarithm of average daily revenue over the past one month. Cumulative variables (e.g. store age, overall rating, percent of positives, mean DSR) are advanced for one month using the Lead ($x_{t+1}$) function of Stata. Binary variables that record whether a seller uses a specific feature (e.g. bundling, shop VIP, warranties, luxurious store web site, detailed pictures) over the past one month are kept in the same period as the dependent variable, because they all immediately affect sales performance. The results indicate that all the signals, except for percent of positives, have a positive and significant effect on sales performance. $R^2$ decreases by 0.285, 0.0278, 0.0001, 0.0031, and 0.011, respectively, when alternatively excluding one signal (in the order of warranty, overall rating,

| Variables[c] | Models[b] 1. Controls | 2. Warranty | 3. Overall rating | 4. Percent of positives | 5. Mean DSR | 6. Web site quality | 7. Full model |
|---|---|---|---|---|---|---|---|
| Lead (store age$_{t+1}$) | 0.156*** | 0.143*** | 0.168*** | 0.133*** | 0.128*** | 0.126*** | 0.134*** |
| | (6.410) | (6.030) | (7.200) | (5.730) | (5.490) | (5.440) | (5.780) |
| Store VIP | 0.162*** | 0.124*** | 0.115*** | 0.100*** | 0.102*** | 0.103*** | 0.099*** |
| | (6.630) | (5.250) | (4.860) | (4.320) | (4.350) | (4.410) | (4.270) |
| Bundling | 0.233*** | 0.182*** | 0.152*** | 0.144*** | 0.145*** | 0.155*** | 0.144*** |
| | (9.920) | (7.920) | (6.480) | (6.250) | (6.270) | (6.810) | (6.250) |
| Time-limited discount | 0.077** | 0.037 | 0.076** | 0.038* | 0.041* | 0.038* | 0.039* |
| | (3.340) | (1.630) | (3.480) | (1.740) | (1.860) | (1.720) | (1.760) |
| Warranty | | | 0.227*** | 0.221*** | 0.234*** | 0.244*** | 0.219*** |
| | | | (8.770) | (8.710) | (9.250) | (9.970) | (8.650) |
| Lead (overall rating$_{t+1}$) | | 0.191*** | | 0.180*** | 0.184*** | 0.186*** | 0.184*** |
| | | (8.700) | | (8.440) | (8.530) | (8.640) | (8.580) |
| Lead (percent of positives$_{t+1}$) | | 0.044* | 0.019 | | 0.043* | 0.039* | 0.038* |
| | | (1.980) | (0.830) | | (1.970) | (1.780) | (1.740) |
| Lead (mean DSR$_{t+1}$) | | 0.123*** | 0.101*** | 0.103*** | | 0.106*** | 0.101*** |
| | | (5.740) | (4.650) | (4.840) | | (5.000) | (4.750) |
| Web site quality | | 0.153*** | 0.097*** | 0.092*** | 0.100*** | | 0.091*** |
| | | (6.000) | (3.650) | (3.540) | (3.840) | | (3.520) |
| Constant | −0.009 | −0.030 | −0.047* | −0.043* | −0.045* | −0.029 | −0.042* |
| | (−0.390) | (−1.380) | (−2.160) | (−2.020) | (−2.100) | (−1.400) | (−1.970) |
| $R^2$ | 0.1958 | 0.2701 | 0.2706 | 0.3018 | 0.2932 | 0.2977 | 0.3031 |
| $R^2$ change[d] | −0.1073 | −0.0330 | −0.0325 | −0.0013 | −0.0099 | −0.0054 | – |

**Notes:** $n = 1{,}589$. [a]The path coefficients in the table are standardized; [b]log (average daily revenue) is the dependent variable, values enclosed inside the parentheses are $t$-values; [c]store age and three reputation indexes are measured at the end of last month, others are binary values over the past month; [d]change in $R^2$ after excluding the corresponding independent variable from the full model. *$p < 0.1$; **$p < 0.01$; ***$p < 0.001$

**Table VI.** OLS regression results[a]

percent of positives, mean DSR, and web site quality) from the full model. The comparison results are identical to those that of PLS and OLS regressions.

In sum, given that hypotheses testing of the three different methods achieved identical results, we conclude that the effectiveness of the five signals in improving sales performance ranks (from high to low) as follows: warranty, overall rating, mean DSR, web site quality, and percent of positives.

## 5. Discussion and conclusion

### *5.1 Discussion of findings*

Signals are becoming an increasingly popular e-marketplace selling tool; little wonder then that signal effectiveness has been attracting research attention (Srivastava and Lurie, 2004). Drawing on signaling theory, our research investigates the different effects of five popular online signal instruments (i.e. warranty, overall rating, percent of positives, mean DSR, web site quality) on the sales performance of e-marketplace sellers. In the context of China's largest e-marketplace, Taobao, we have analyzed, predicted, and ranked these five signals according to their effect on sales performance (from the highest to the lowest): warranty, overall rating, percent of positives, mean DSR, and web site quality.

| Variables[c] | Models[b] 1. Controls | 2. Warranty | 3. Overall rating | 4. Percent of positives | 5. Mean DSR | 6. Web site quality | 7. Full model |
|---|---|---|---|---|---|---|---|
| Lead (store age$_{t+1}$) | −0.090 | −0.061 | −0.112 | −0.121 | −0.187 | −0.148 | −0.129 |
| | (−0.280) | (−0.200) | (−0.360) | (−0.390) | (−0.600) | (−0.480) | (−0.420) |
| Store VIP | 0.056*** | 0.053*** | 0.053*** | 0.049*** | 0.049*** | 0.048*** | 0.050*** |
| | (6.760) | (6.620) | (6.580)*** | (6.260) | (6.140) | (6.110) | (6.270) |
| Bundling | 0.031*** | 0.027*** | 0.025*** | 0.025*** | 0.025*** | 0.026*** | 0.025*** |
| | (5.480) | (4.950) | (4.560) | (4.520) | (4.530) | (4.820) | (4.510) |
| Time-limited discount | 0.012** | 0.012** | 0.010* | 0.011** | 0.012** | 0.010** | 0.011** |
| | (3.020) | (3.100) | (2.440) | (2.730) | (2.990) | (2.600) | (2.730) |
| Warranty | | | 0.131*** | 0.107*** | 0.115*** | 0.110*** | 0.107*** |
| | | | (16.050) | (13.150) | (13.980) | (13.520) | (13.150) |
| Lead (overall rating$_{t+1}$) | | 0.105*** | | 0.097*** | 0.099*** | 0.094*** | 0.096*** |
| | | (22.830) | | (20.890) | (21.110) | (20.380) | (20.860) |
| Lead (percent of positives$_{t+1}$) | | −0.011 | −0.014* | | −0.010 | −0.011 | −0.011 |
| | | (−1.330) | (−1.700) | | (−1.180) | (−1.340) | (−1.320) |
| Lead (mean DSR$_{t+1}$) | | 0.079*** | 0.079*** | 0.077*** | | 0.078*** | 0.077*** |
| | | (21.660) | (21.370) | (21.110) | | (21.480) | (21.120) |
| Web site quality | | 0.036*** | 0.025*** | 0.032*** | 0.038*** | | 0.032*** |
| | | (7.670) | (5.430) | (7.000) | (7.980) | | (7.000) |
| Constant | 0.000 | −0.848*** | 0.000 | −0.779*** | −0.800*** | −0.760*** | −0.778*** |
| | (0.000) | (−22.760) | (0.000) | (−20.820) | (−21.040) | (−20.310) | (−20.790) |
| $R^2$ | 0.0062 | 0.0587 | 0.0594 | 0.0871 | 0.0841 | 0.0762 | 0.0872 |
| $R^2$ change[d] | −0.081 | −0.0285 | −0.0278 | −0.0001 | −0.0031 | −0.011 | – |

**Table VII.**
Fixed-effects model results[a]

**Notes:** $n = 15{,}890$. [a]The path coefficients in the table are standardized; [b]log (average daily revenue) is the dependent variable, values enclosed inside the parentheses are $t$-values; [c]store age and three reputation indexes are measured at the end of last month, others are binary values over the past month; [d]change in $R^2$ after excluding the corresponding independent variable from the full model. *$p < 0.1$; **$p < 0.01$; ***$p < 0.001$

Our work makes several important contributions. First, our findings on the significant relationships between signal instruments (warranty, overall rating, web site quality) and sales performance echo previous research (Bockstedt and Goh, 2011; Li *et al.*, 2009; Ou and Chan, 2014). Second, mean DSR is a relatively new reputation index, which has thus far received limited research attention. Wang *et al.* (2013) examined the impact of DSR on store survival and our study has examined its relationship with sales performance. Consistent with our prediction, the results indicate that DSR significantly influences sales performance. Third, our results on the relationship between percent of positives and sales performance are consistent with previous studies in different contexts; thus, providing further evidence of the marginal effect of percent positives in reducing the information gap between buyers and sellers and improving sales performance (Bockstedt and Goh, 2011; Ou and Chan, 2014). Fourth, although several recent studies have examined the impacts of different signal instruments on actual sales performance, they have not compared the relative effectiveness of these signal instruments (Bockstedt and Goh, 2011; Li *et al.*, 2009; Ou and Chan, 2014), leaving an open question of great practical importance to sellers.

Most of the results are consistent with our theoretical predictions, except for two pairs of comparison: percent of positives vs mean DSR (*H7*) and percent of positives vs

web site quality (*H9*). To understand the unexpected weaker impact of percent of positives over mean DSR and web site quality, we first examined the distribution of the variable percent of positive. It is worth noting that the distribution of percent of positives was extremely skewed toward a high mean value of 99.7 percent and a low standard deviation of 0.006. We then verified the reliability of the values by referring to prior studies and found that our results are consistent with previous findings (i.e. regarding the increase of reputable sellers in the e-marketplace) (Bockstedt and Goh, 2011; Clemons, 2007; Dellarocas and Wood, 2008). There may be two reasons for the high value of percent of positives. First, the feedback system widely used in the e-marketplace is optional, which may cause biased reporting. For example, Li (2010) found that only half of consumers leave feedback after transactions. Second, consumers may leave positive feedback in fear of retaliation or harassment from the seller if they provide an unfavorable rating or because the seller offers incentives in exchange for positive feedback. Thus, we reason that percent of positives has a weaker effect (than mean DSR and web site quality) because it has been boosted to an excessively high level, but with a very low standard deviation. As a result, consumers find it difficult to perceive the cost of the marginal increase in the value of percent of positives. In contrast, although the value of mean DSR was also skewed toward the high end (4.731), it has a higher standard deviation (0.753) than percent of positives, making it possible for consumers to perceive and comprehend the associated cost with improving mean DSR. Consumers can easily observe differences among sellers when it comes to the two dimensions of web site quality (i.e. luxurious web site template and detailed pictures of products); thus, consumers recognize the costs associated with high web site quality and they rely on web site quality to evaluate product quality, with flow-on impacts on sales performance.

### *5.2 Implications for research*

This study offers four key departures from past studies. First, the early e-commerce signaling literature concentrated on investigating the effects of a specific type of signal on consumers' perceptions of product quality (Biswas *et al.*, 2009; Gregg and Walczak, 2008), risks (Alicia and Esther, 2011; Biswas and Biswas, 2004), trust (Alicia and Esther, 2011; Arnold *et al.*, 2007; Bolton *et al.*, 2008; Lee *et al.*, 2005; Wang *et al.*, 2004), and purchase intention (Gregg and Walczak, 2008; Wells *et al.*, 2011). Scholars have recently empirically examined the relationship between signals and sellers' actual sales performance in different contexts; however, no work has been done to date to theoretically and empirically compare the relative effectiveness of each signal in enhancing sales performance. By conducting a large-scale empirical analysis in the same context as Ou and Chan (2014), we have contributed to the signaling literature by responding to the call to examine the relative effectiveness of different signaling instruments in a specific context (Srivastava and Lurie, 2004). Second, our work also adds to the e-marketplace literature by providing insights into how e-marketplace sellers use the instruments designed by e-marketplace platform providers (e.g. warranties, online reputation indexes, visually appealing web sites) as signals to address information asymmetry and as a way of standing out from fierce competition (Bockstedt and Goh, 2011; Li *et al.*, 2009). Third, our study reveals how these instruments serve different functions in contributing to actual sales performance in the e-marketplace. Our work is the first to reveal that warranty has the largest effect on sales performance, followed by online reputation indexes, and web site quality. Finally,

this study extends the applicability of signaling theory to the e-marketplace context by incorporating the distinctive features of the e-marketplace platform. As such, signaling theory will now be a very useful theoretical tool for investigating the effectiveness of different signaling strategies in the e-marketplace context.

### *5.3 Implications for managerial practice*

It is important to note that the underlying mechanism that drives our hypotheses is grounded in solid theory (i.e. signaling theory), even though the hypotheses are argued in the context of Taobao. The theory remains powerful in differentiating the effectiveness of signals beyond the context of the present study, even though other e-marketplaces may have their own idiosyncratic designs or features. In this regard, our study not only addresses the relative effectiveness of these signals in China's largest e-marketplace, but also demonstrates the efficacy of signaling theory in analyzing commonly used signals in e-marketplaces in general. The results provide specific guidelines for e-marketplace sellers on where to allocate their efforts to build up these different signaling instruments to gain the largest effect on sales performance.

First, our results show that warranty can significantly affect sales performance in the e-marketplace, with disciplinary mechanisms of prevailing strength. Thus, a seller with high-quality products but a tight budget can largely depend on this type of signal to enhance sales performance. Our results suggest that these types of sellers should enroll in warranty schemes such as money-back guarantee, compensation for fake products and so on and display this warranty information on their web site.

Second, our findings can also help sellers choose select their strategies for investing in reputation indexes. The results indicate that, among the three reputation indexes, overall rating is most effective in improving sales performance, mean DSR comes second, and percent of positives has a marginal effect. Thus, sellers might quickly improve their overall rating by launching some immediate promotions, then pay close attention to a specific aspect of their reputation (i.e. product quality, distribution, or service) to enhance performance at a lower cost. Percent of positives should be kept relatively high (e.g. above the mean value 99.7 percent).

Third, our results indicate that web site quality enhances sales performance. Transaction platform should provide sellers with simple and easy-to-use features that increase the consumer appeal of the web site and intuitively provide accurate product information. Sellers must ensure that their only point of contact with consumers – their store web site – is as high quality as possible by creatively deploying platform features and constantly enhancing the web site's visual appeal.

### *5.4 Limitations and future research*

This study has several limitations. First, it focussed on sellers in one transaction platform (Taobao). This may limit the generalizability of the findings and we recommend that future studies extend to other e-marketplace contexts. Second, our studied e-marketplace sellers used a combination of several signals to improve their performance. Thus, it is difficult to discern the effects of a single signal. Future research should investigate the use of multiple signals (e.g. signaling strategies) because it is an important and common sales approach in e-marketplaces. Third, the use of signals by e-marketplace sellers is dynamic, because of age and scale. Consequently, the relationships between signal and performance are also dynamic. Current analysis

methods are of limited use in this case and future studies should employ more advanced methods that better cater for such dynamic relationships.

In conclusion, this study has examined the different effects of signals on the sales performance of e-marketplace sellers. The results indicate that: first, all the studied signals – warranty, overall rating, percent of positives, mean DSR, web site quality – positively affect seller sales performance, although the effect of percent of positives is marginal; and second, of the five signals, warranty has the highest effect on sales performance, followed by overall rating, mean DSR, web site quality, and percent of positives. This pioneering study contributes to the theory and practice of e-marketplace signals and seller performance, and opens up opportunities for future research into the effects of different signal combinations (e.g. the various signaling strategies of e-marketplace sellers).

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