The Impact of Social Media Signals on Supplier Selection: Insights from Two Experiments

Dr Aneesh Banerjee

Cass Business School, City, University of London

106 Bunhill Row, London, EC1Y 8TZ

Dr Jörg Ries

Cass Business School, City, University of London

106 Bunhill Row, London, EC1Y 8TZ

Prof Caroline Wiertz

Cass Business School, City, University of London

106 Bunhill Row, London, EC1Y 8TZ

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Abstract

Purpose: Online B2B markets offer buyers a new source of information provided by social media signals about suppliers. These signals have not yet received much attention in the supplier selection literature. This study advances our understanding of how buyers respond to social media signals in the supplier selection process.

Design: We develop a choice-based conjoint experimental design to isolate and manipulate two signals from social media: volume (i.e. the number of ratings) and valence (i.e. average evaluation of the ratings). We test how these signals are interpreted in the context of varying deal sizes and price points.

Findings: Both volume and valence are positively correlated with supplier selection. However, (i) the signals exhibit diminishing returns and (ii) the efficacy of valence is interpreted in the context of volume. We also find that (iii) there is no influence of the deal size and that (iv) the relationships between signals and supplier selection are negatively moderated by deviations from the reference price.

Implications: Social media signals should be considered in supplier selection decisions as they convey valuable information to the buyer. However, signals go through a process of interpretation which has implications for buyers, suppliers, and owners of online B2B markets.

Originality: Our research opens new lines of inquiry in behavioural operations management research regarding the mechanisms by which buyers interpret social media signals and how these ultimately influence their choice.

Keywords: *Supplier selection, B2B markets, Social media, Product reviews, eWOM, Valence, Volume, Signalling theory*

1. Introduction

The increasing dependency on a global supply network has made identification and selection of suitable suppliers central to the competitiveness and innovativeness of firms (Rao and Holt, 2005; Soosay et al., 2008). Accordingly, the supplier selection problem has received considerable attention in recent years (Ho et al., 2010; Wetzstein et al., 2016). Much of the research in this area tends to focus on identifying relevant selection criteria (e.g. quality, reliability or cost) and developing approaches for selecting preferred suppliers given available preference and performance information as well as a set of non-dominated suppliers (cf. Wetzstein et al., 2016).

More recently, with almost 50% of all buyers searching for new suppliers online (WLW, 2017), the emergence of online business-to-business (B2B) markets has opened new opportunities as well as challenges for supplier identification and selection. On the one hand, buyers can more easily adopt a global sourcing approach and engage with a global market of suppliers. Besides, they can also benefit from additional supplier-related information available from social media peer evaluations (Balocco et al., 2010). On the other hand, selecting suppliers in an online B2B market creates new challenges. Buyers now effectively deal with a much larger sample of suppliers as well as increased information asymmetry (Steinle et al., 2014). In an online B2B market, buyers are unable to physically evaluate the quality of products, to assess the trustworthiness of the supplier, or even to predict possible cultural barriers. Therefore, buyers need to invest additional resources to gather more detailed information about potential suppliers.

In such situations, buyers rely on 'signals' to bridge some of the information asymmetry inherent in online marketplaces. Signals are "activities or attributes of individuals [suppliers] in a market which, by design or accident, alter the beliefs of, or convey information to, other individuals [buyers] in the market" (Spence 1974: 1, square brackets added). In an online B2B market, suppliers give out various intentional signals to buyers (e.g. certifications), but the emergence of unintentional social media signals generated by other buyers also promises to be a useful source of additional information for the supplier selection process. Often called electronic word of mouth (eWOM) in the marketing literature, these social media signals have two main characteristics: volume, which is the amount of social media feedback from existing buyers (i.e. the number of ratings), and valence, which is the sentiment of the social media feedback (i.e. average evaluation of the ratings) (cf. Floyd et al., 2014). These two social media signals have been found to impact sales in business-to-consumer (B2C) markets, but their respective influence is dependent on several contingency factors (Babić Rosario et al., 2016). Furthermore, as discussed in more detail later, there are some key difference in what drives supplier selection decisions in B2B markets compared consumer choices in a B2C markets. Most notably in B2C markets, consumers are heavily influenced by the brand of the product (Ho-Dac et al., 2013), whereas organisational buyers are much less concerned with the brand, instead they pay more attention to the importance and complexity of the purchase (Luzzini et al., 2012). Their supplier selection decisions are therefore more likely affected by financial considerations such as deal size and price (Brown et al., 2011).

In response to the Special Issue call (Cheng et al., 2019), this study therefore aims to answer the following questions: How are organisational buyers influenced by unintentional signals generated from social media, specifically (i) the number of ratings indicating *volume* and (ii) the average rating indicating *valence* – when scanning for suppliers in online B2B markets? How do different purchasing scenarios, such as deal size and product price, interact with social media signals to influence supplier selection? Given the increasing importance of online B2B markets for identifying suitable suppliers and efficiently handling purchase processes, this paper contributes to supplier selection research by exploring the role of social media signals in reducing information asymmetry in online B2B markets. We also contribute to behavioural research in operations management by opening new lines of inquiry into the mechanisms through which buyers interpret social media signals and how these ultimately influence their choice (Tokar, 2010). Our findings provide valuable insights for buyers, suppliers and market owners.

In the following sections, we review the current research on supplier selection, signalling theory, and the use of social media in B2B markets and develop testable hypotheses about the influence of social media signals on buyers. Next, we describe our experimental set-up, data, and present our findings. In the final sections, we discuss our findings in the light of implications for research on the use of social media in online B2B markets as well as implications for practitioners – suppliers, buyers, and market owners and close with conclusions and limitations.

2. Literature review

2.1 Supplier selection process and criteria

The supplier selection process has received considerable attention in past years (Ho et al., 2010; Wetzstein et al., 2016). This process typically includes the identification of needs and specifications that can be translated into a set of criteria used to evaluate, monitor and develop suppliers that have been identified through supply market research and/or RFX (Request for Information/Proposal/Quote). Following an initial assessment and qualification, short-listed suppliers undergo a more detailed evaluation before being potentially selected as actual supplier (Zimmer et al., 2016). A large share of the supplier selection research has focussed on identifying relevant selection criteria and on developing quantitative approaches for selecting preferred supplier(s) given some preference and supplier information as well as the set of non-dominated suppliers along the conflicting criteria (Wetzstein et al., 2016). Many different selection criteria have been proposed in the literature, including quality, delivery speed and dependability as well as cost (Ho et al., 2010). More recently, some studies have also focussed on economic and environmental sustainability criteria even though social sustainability has largely been overlooked (Zimmer et al., 2016). Another criterion that has been overlooked till date is the availability of information about a supplier from other buyers as provided by social media. This aspect, however, is of particular interest as supplier selection decisions are influenced by the decision maker's perception of uncertainty and available signals (Kull et al., 2014).

2.2 Signalling theory in B2B markets

Signalling theory proposes that to alleviate some of the risk and uncertainty of dealing with unknown sellers, buyers will screen sellers using observable, useful, and trustworthy signals. First, these signals must be clearly observable. In online B2B markets, suppliers prominently display intended signals like certifications, guarantees, and selected customer testimonials, as well as unintended signals that they do not fully control such as 'top supplier ranking' or social media feedback. Second, these attributes are useful for buyers – albeit the attributes convey specific information about the supplier that may or may not be equally important for all buyers. For instance, a sustainability certification that a supplier displays on their profile may not be important for some buyers in selecting suppliers. Finally, for the signals to be credible and create a useful separation between suppliers that have the attribute and suppliers that do not, they must be trustworthy and costly. For instance, everything else remaining equal, a supplier with a reputable quality certification is more likely to have better quality than a supplier without any certification. However, different receivers can view or 'calibrate' the same signal differently and therefore these signals go through a process of interpretation into perceived meaning by buyers (Branzei et al., 2004). For sellers in online B2B markets, this implies that they should generate multiple signals to convince potential buyers of their credibility.

Intentional signals: A common approach for sellers is to generate multiple signals intentionally by acquiring different certifications. For instance, an intentional signal for quality is the quality certification ISO 9000 that meets all the criteria set out by signalling theory (Connelly et al., 2011). Similarly, suppliers can join industry initiatives to signal their commitment to common guidelines for social, environmental or economic practices and sharing related information. The intermediary Sedex, for instance "helps buyers and suppliers to share and exchange data, helping to better manage social and environmental risks within their supply chain, and positively impact responsible sourcing" (Sedex, 2019). Suppliers can also generate intentional signals by introducing trade policies that lower the risk for buyers. For instance, a supplier can offer 'Trade Assurance' – an increasingly popular assurance that lesser known suppliers offer to overcome trust issues. Finally, a supplier can also generate intentional signals by prominently highlighting customer testimonials – especially from well-known customers. In all these instances of intentional signalling, the supplier is in control on whether to provide these signals or not.

Unintentional signals: There are also unintentional signals that are not fully under the supplier's control. One such unintentional signal is the feedback generated about the supplier on social media.

Most online B2B markets follow-up with buyers to leave feedback for suppliers. This feedback is usually in the form of ratings on various attributes of the supplier on a five-point scale and a free text section. The online B2B market then aggregates the feedback into two main metrics: the number of ratings that indicates *volume* (i.e. the number of buyers who have given feedback) and the average rating that indicates *valence* (i.e. the sentiment of the feedback). This social media feedback is prominently displayed on the supplier's profile and importantly, the supplier cannot remove it if it turns unfavourable. Signals generated from social media ratings also meet all the criteria set out by signalling theory. First, these aggregated ratings are prominently displayed on the profile page of the supplier. Second, they are useful as they help future buyers understand the satisfaction of past buyers dealing the supplier as well as estimate the popularity of the supplier. And finally, they are costly to produce because the supplier must meet the buyer's expectations to be able to achieve a good rating.

Online communication between current and potential customers (also labelled as eWOM) has become an important area of research for marketing scholars. There are several recently published review papers that summarize the marketing literature to date and highlight the influence of customer reviews on future sales (Babić Rosario et al., 2016; Purnawirawan et al., 2015). The most recent meta-analysis by Babić Rosario et al. (2016) found that across 96 studies conducted in a B2C context, eWOM is consistently linked to increased sales, particularly in the context of e-commerce platforms. Overall, this effect is driven more strongly by eWOM volume than eWOM valence, however, the authors note that the combined effect of eWOM volume and valence on consumer behaviour is complex. For example, Khare, Labrecque and Asare (2011) study the volume effect in the context of consumers' movie choices. The volume effect posits that a high volume of reviews accentuates the effect of review valence so that a higher volume of negative reviews has a stronger negative effect and a higher volume of positive reviews has a stronger positive effect than a low volume. While this stream of research is useful for our analysis of signals in B2B markets, especially in interpreting our results, there are several important differences between signalling in B2B markets compared to B2C markets that are worth highlighting.

Differences in signalling in B2B v B2C markets: In general, communication in B2B markets involves sellers (suppliers) attempting to communicate relatively complex ideas to specialized and smaller audiences (buyers), while in B2C markets, the seller typically communicates relatively simple ideas to large audiences. Therefore, sellers in these two types of markets tend to choose different signals to communicate with their audiences. In the case of screening B2B markets, the seller's brand or company is likely to be unknown to the buyer, therefore the seller is likely to rely on acquiring specialized and better-known certifications (e.g. ISO 9000) to appeal to a target segment, whereas in B2C markets the seller is more likely to highlight or build on its own brand as a differentiator. An important distinction between these two signals is that the same certification can be acquired by more than one supplier in B2B markets – but brands in B2C markets would always be distinct and remain a key identifier for an individual supplier. Brands in B2C markets not only act as a signal in themselves, but they also impact how consumers respond to unintentional signals, such as social media reviews. Mafael, Gottschalk and Kreis (2016) have found that brand attitude is indeed very important in determining how consumers process eWOM information, so that if they have a positive attitude towards the brand, they find positive arguments in an eWOM review more persuasive and negative arguments less persuasive than if they have a negative attitude towards the brand. Such biased information processing of social media signals would be less likely to occur in B2B markets.

The transaction value in these markets is also substantially different. Buyers in B2B markets typically engage in much higher value transactions – therefore both the trading risk and value appropriation risk are much higher compared to B2C transactions (Lanzolla and Frankort, 2016). Furthermore, as buyers in B2B markets are not buying for their personal consumption but they are buying for their firm, they are more likely to keep personal tastes aside and pay greater attention to both intentional and unintentional signals. For instance, they are more likely to follow a process or 'checklist' for choosing suppliers that may consist of checking for minimum quality certifications, trade assurances, or even size of the business to estimate long-term viability. In a similar vein, buyer's individual differences (e.g., need for uniqueness, Khare et al., 2011) will play less of a role in B2B buying decisions because the buyer is purchasing on behalf of the company and not to enhance his/her own identity. Buyers in B2B markets are therefore expected to be more objective in their interpretation of social media signals and less likely to be influenced by idiosyncratic preferences when buying for their business.

Finally, there are differences in the type of social media communication common in B2B compared to B2C markets (Swani et al., 2014). In addition to the numerical five-point feedback, consumers in B2C markets are more likely to leave text-based feedback in the form of online reviews. In contrast, buyers in B2B are not as likely to take the time to leave text-based feedback. Consulting companies that provide advisory services in this area argue that this is because the text-based feedback is usually not anonymous and therefore buyers do not want to give negative feedback that could hurt their professional relationship with the supplier (see for example Koble, 2018; StratoServe, 2019). This behaviour makes the communication between current and future buyers more focused on numerical social media feedback that is displayed on the seller's profile.

<u>Importance of social media signals in B2B markets:</u> As many suppliers acquire the same intentional signals, buyers are likely to pay a lot of attention to unintentional signals to narrow down their search. One such signal is the aggregated social media ratings (i.e. volume and valence of ratings) generated by other buyers. Clearly, when a supplier has both high volume and valence, this combination becomes a dominant signal – but what happens when either volume or valence is low? We know from the B2C literature that generally, volume tends to influence the interpretation of valence (Babić Rosario et al., 2016), but we do not know how these two signals are traded off, especially in cases in which volume does not yet dominate. Therefore, the key question is: When sellers have similar characteristics and the same intentional signals, how do buyers interpret the signal generated from differences in volume and valence of ratings? Our intent is to understand how changes in these signals generated by social media influence the chances of a supplier getting selected in the context of different deal sizes and reference prices. This is particularly important for suppliers who have a low transaction volume and thus by extension less opportunity to receive a high volume of ratings, and for new suppliers who have not yet had enough time to generate a high volume of ratings. Understanding the pay offs for increasing volume or valence of ratings can help guide suppliers' social media

strategy in online B2B markets. In addition, this understanding is also important for buyers to effectively integrate social media signals into their supplier selection processes, and for online market owners to govern the flow of information between suppliers and buyers.

3. Hypotheses development

3.1 Diminishing returns

Based on signalling theory (Spence, 1974, 2002), we have argued that since the quality of unknown suppliers cannot be directly observed, buyers would aim to reduce the information asymmetry and rely on information signals that are thought to correlate with quality of the supplier. In online B2B marketplaces, volume and valence of buyer ratings convey such signals. Volume indicates the number of buyers that have previously engaged that supplier – so higher volume indicates that the supplier is more popular. Valence indicates the average satisfaction of previous buyers with that supplier – so higher valence indicates greater satisfaction with that supplier. Therefore, in line with signalling theory we expect that the likelihood of selecting a supplier is directly linked to volume and valence signals of that supplier.

Since volume and valence signals serve as approximations of the quality of the supplier, buyers are indeed likely to be sensitive towards more information to improve the accuracy and validity of the signals (Aydinoğlu and Krishna, 2011, Drover et al., 2018). However, we do not expect this relationship to be linear as buyers are likely to benefit more from changes in the signal at the lower end compared to the higher end of these signals. For example, 10 additional reviews are more useful for the buyer’s assessment of the signal’s strength when volume is 25, compared to when volume is 250. Griffin et al. (2004) propose a cognitive model of information sufficiency in decision-making that is useful in understanding the basis of these differences in signal interpretation. They argue that individual decision-makers have a desired level of *judgement-confidence*: the strength of a signal that would be deemed satisfactory in making a decision with a certain level of accuracy and validity. Therefore, for individual decision-makers, an increase in signal strength at the lower end is more useful till it attains the desired level of judgement-confidence, compared to an increase in signal strength at the higher end – after it has surpassed their judgement-confidence.

This stream of research points out that every individual has an idiosyncratic threshold level of judgement-confidence, but it is estimated to be consistent for a person (Drover et al., 2018). As the signal increases in value, more respondents will cross their own threshold level of judgement-confidence and increasingly, the positive influence of the signal on decision-makers would diminish. Therefore, we hypothesise that the positive influence of volume and valence on buyers has diminishing returns as more buyers cross their threshold judgement-confidence.

H1: The positive influence of signals from volume and valence of social media has diminishing returns.

3.2 Supremacy effect of volume over valence

When evaluating suppliers, buyers take into account a combination of both signals. This evaluation is easy when both volume and valence are high or when both are low. However, in situations when the two signals oppose each other, it is not clear which signal is more effective in influencing buyers' decisions. To understand this question, we consider buyers' preferences towards two opposing supplier profiles: when one of the signals is high while the other is low, and vice versa.

We know that while valence is a signal of average satisfaction of previous buyers, volume enables future buyers to qualify and interpret the accuracy of this valence signal (Khare et al., 2011). Put differently, a buyer would have greater uncertainty in assessing the true satisfaction level with a supplier that has received high valence and low volume ratings compared to a supplier with low valence and high-volume ratings– even though the mean valence may be lower for the latter supplier. In these situations, buyers are likely to select a supplier with lower uncertainty when they are making purchasing decisions. The link between decreasing uncertainty with increasing volume has its roots in the 'wisdom of the crowd effect': the statistical observation that assessment of a large number of people can indeed be close to the true representation (Prelec et al., 2017). While decision-makers are aware that preferences of single buyers may vary, the aggregation of numerous buyers is likely to nullify both positive and negative variation to generate a more accurate estimate (Lorenz et al, 2011). In essence, buyers interpret the accuracy of valence based on their assessment of what they would consider a suitably large sample (Babić Rosario et al., 2016). Therefore, we hypothesise:

> *H2: Both opposing signal combinations, i.e. high volume with low valence and low volume with high valence, negatively influence the buyer's decision compared to a base combination; but the combination of low volume with high valence has a stronger negative influence than the combination of high volume with low valence.*

3.3 Sensitivity of social media signals to deal size

Prior research indicates that organizational buyers are sensitive to risk (Brown et al., 2011). Therefore, their interpretation of social media signals is likely to be influenced by the size of the deal as buyers' assessment of expected loss is dependent on the probability of a loss and its significance: expected loss = risk of loss * value of the deal (Mitchell, 1995). A larger deal size indicates higher expected losses from the risk of an unsatisfactory outcome as compared to a smaller sized deal.

Prospect theory is useful in understanding the behaviour of buyers as the deal size changes. The central idea of *loss aversion* in decision making suggests that faced with a risky choice that can lead to losses, individuals are more likely to seek options that avoid losses even if these options have lower utility (Kahneman and Tversky, 1979). Therefore, buyers are likely to be more sensitive to volume and valence signals when considering a larger deal. Put differently, they are more likely to favour higher volume and valence as it indicates relatively less risk in a large deal size purchasing decision compared to a small deal size purchase decision. In the same vein, buyers are more likely to more strongly disfavour lower volume and valence in a large deal situation as it indicates greater potential impact. Therefore, we expect that the size of the deal will positively moderate the influence of volume and valence signals on supplier selection decisions.

> *H3: Deal size will positively moderate the influence of volume and valence signals.*

3.4 Sensitivity of social media signals to reference price

Another important factor that could influence the interpretation of social media signals is price because buyers in online marketplaces have to balance finding the best possible product with their available budgets. Extant literature shows that buyers are heavily influenced by reference prices: an internal price standard that buyers would deem suitable for the goods or service in question (Monroe, 1973). Reference prices are formed from prior experience of purchasing similar goods or services, or by comparing similar products in the market (Mazumdar et al., 2005). Drawing upon research on decision making under risk and uncertainty, scholars studying purchasing in B2B markets have proposed that a price that is close to the reference price indicates an expected price for the buyer. If the price offered by a supplier is above the reference price, the buyer is at 'loss' and if the price offered by the supplier is lower than the reference price then the buyer is at 'gain' (Bruno et al., 2012). This suggests that the way buyers interpret social media signals when the price is within their reference price expectations would be different from when the price is higher or lower than the reference price.

When the price is above the reference price, buyers sense a loss scenario – unless the price premium indicates superior quality. However, due to the inherent risk in social media signals, buyers are more likely to downplay the signals and avoid the higher price option. Prior research on subcontractor choices provides further insights into buyers' loss aversion behaviour. For instance, Biong (2013) shows that due to the inherent risks involved in assessing reputation signals, buyers are unwilling to pay a price premium for subcontractors even when they have a better reputation. This indicates that the efficacy of the social media signals would reduce as the supplier's price goes above the reference price. Conversely, when the supplier's price is below the reference price, buyers perceive a gain scenario and are more likely to select this option. Their mindset will shift from loss aversion to *gain seeking*, which implies that decision-makers are motivated by goals to pursue gains and are therefore likely to take risks to pursue their goals (Rhee and Fiss, 2014). In a gain seeking mindset, buyers underplay the efficacy of social media signals in favour of the gains from a lower price. Therefore, we would expect that price below the reference price would also negatively moderate the relationship between social media signals and supplier selection. Put together, we expect:

H4: Lower and higher price, compared to a reference price, negatively moderates the influence of volume and valence signals on supplier selection.

4. Methodology

4.1 Experimental design

Experimental research designs to understand decision-makers' behavioural preferences are becoming more common in operations management (see for example Deck and Smith, 2013; Petropoulos et al., 2018). To test our hypotheses, we develop a Choice-Based Conjoint (CBC) experimental design. CBC is an appropriate design for two main reasons. First, as Levitt and List (2007: 153) mention, experimental designs in general and CBC in particular "provide *ceteris paribus* observations of individual economic agents, which are otherwise difficult to obtain". By fully embracing the controlled environment of the experimental set-up, we can isolate and regulate the levels and attributes of interest, keeping everything else equal. Second, CBC provides insights into decision-makers' behaviours and preferences towards, and trade-offs between, different attributes. Such a design therefore allows us to estimate how these preferences are likely to change with varying levels of the different attributes (Orme, 2010).

We follow the directions of Rao (2014) in setting up a CBC experimental design. Table 1 shows the attributes and levels we used to design the two experiments we conducted. To identify suitable levels of volume and valence, we browsed through three commonly used online B2B markets (Alibaba, Amazon B2B, and GlobalSources). We found that valence typically starts from 3.5/5.0 and can be as high as 5.0/5.0. We decided to restrict our valence levels from 3.5 to 4.5, as valence above 4.5 represents a dominantly positive signal. Thus, we set the levels of valence as 3.5, 3.7, 3.9, 4.1, 4.3 and 4.5. We found that volume can also vary significantly from less than 10 to over 500, therefore, we selected the volume levels as 10, 25, 50, 100, 250, 500. We decided not to have a linear scale for volume as we wanted to cover a broader range while having more levels at the lower end of the spectrum.

These attributes and levels were then used to generate orthogonal choice sets with four options in each choice scenario and twelve choice scenarios per respondent. The orthogonal choice sets were created using the CBC design and analysis software Sawtooth. In every choice scenario, the respondent was asked to select the most preferred supplier from four non-dominant options. Each respondent was asked a set of demographic questions as well as an attention check question after completing the CBC questions. Respondents were also asked to leave an open-ended text-based response explaining their decision rules for selecting a supplier. Our chosen purchasing context is that of a buyer seeking a supplier of 3D printers. This is a suitable context as the product is not sector-specific, presents an adequate level of complexity while still being comprehensible, and provides us the scope to create a variety of purchasing scenarios varying price and deal size.

Insert table 1 here

To test our hypotheses, we conducted two experiments. In experiment 1, respondents were asked to trade off volume and valence signals only. In this experiment, we manipulated deal size using two conditions (i) Select a supplier to buy one 3D printer with a budget of £2,000 and (ii) Select a supplier to buy fifty 3D printers with a budget of £100,000. Respondents were randomly assigned to either condition. In experiment 2, we added price as an additional attribute, and respondents were asked to trade-off volume, valence, and price. In this experiment, we set a reference price zone for the respondents as it is common for purchasing manages to have such knowledge. Respondents were informed that "From experience, you know that a 3D printer of your specification typically costs between £1,500 and £2,500". We manipulated price using three levels: (i) £ 1,000, i.e. below the reference price, (ii) £ 2,000, at the midpoint of the reference price, and (iii) £ 3,000, above the reference price.

4.2 Participants

Participants for the CBC were identified using the Prolific online survey platform, a community that is commonly used by researchers to run specialized surveys. We used a two-step process to ensure high quality respondents. First, we created a pre-screening survey to identify a sample of 750 respondents with prior B2B purchasing experience. Second, these respondents with prior purchasing experience were invited to complete the full CBC experiment online. Each respondent was paid £2.00 to complete the survey. Of the 750 eligible participants, 592 completed one of the experiments. We eliminated 83 respondents who did not pass the attention checks. In total, there were 371 valid respondents in experiment 1 (condition 1: n=192; condition 2: n=179) and 138 valid respondents in experiment 2. Table 2 provides descriptive details of the final valid sample – especially with regards to purchasing experience of the participants. From table 2, we see that our samples for each experiment and the two conditions of experiment 1 are well balanced.

Insert table 2 here

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5. Findings

5.1 Descriptive observations

To understand how buyers interpret signals, we start with a part-worth utility analysis and the relative importance of attributes. This analysis was done using Sawtooth Software's part-worth utilities and relative importance analysis package. Similar analytical techniques are common for CBC designs in a variety of fields, including operation management, and are useful to understand the utilities of the attributes at different levels (Venkatesh et al., 2012). Part-worth utilities are numerical scores that measure how much each attribute and level influenced the buyer's decision to make that choice (Hair et al., 2013). Part-worths are scaled to an arbitrary additive constant within each attribute so that the sum of the utilities is zero for that attribute. The marginal utility indicates the change in part-worths per unit change in the levels. The relative importance measure indicates what difference each attribute makes regarding the total utility of a product. The percentages are calculated to obtain a set of attribute importance values that add to 100 percent.

Table 3 displays the part-worth utilities and relative importance of each attribute and level. There are three main takeaways from Table 3. First, we can observe that the marginal utilities for both volume and valence decrease at higher levels of these attributes. For instance, the marginal utility for unit changes in volume is between 0.43 and 0.47 when volume changes from 50 to 100 across all the experimental designs, but it is only between 0.04 and 0.05 for volume changes from 250 to 500. We observe a similar pattern for valence: the marginal utility from increasing valence at higher levels is lower. An analysis of the marginal utility for valence shows that the marginal utility is highest when valence increases from 3.9 to 4.1 across all the experimental designs, indicating that buyers are particularly sensitive to the transition from 3.9 to 4.1 as a benchmark. However, there is a sharp fall in the marginal utility after 4.1. Second, we find that the deal size has little impact on the utilities and relative importance of volume and valence signals. Third, we find that even though volume is relatively more important than valence in the two instances of experiment 1 (Volume 52% v. Valence 48%); upon introducing price as a third attribute in experiment 2, valence becomes relatively more important than volume (Volume 33% v. Valence 38%). This indicates that when the same product is offered at higher or lower prices, buyers are likely to compromise on volume signals more than they are willing to compromise on valence signals.

Data obtained from CBC experimental designs can also be used to run sensitivity analyses to reveal how the share of preference of a supplier (vis-à-vis other suppliers) changes by changing attribute levels one at a time. As Orme (2010: 81) points out “in this way, the impact of each attribute level is estimated within the specific and appropriate context of the competitive landscape.” We used Sawtooth Software’s market simulator package to simulate the changing share of preference for a supplier (Supplier 1) while keeping characterises of the competitor (Supplier 2) constant. While sensitivity analysis can be done for any combination of suppliers, we decided to run the simulation with an established, non-dominant competitor (Supplier 2) with fixed characteristics Vol = 250, Val =

3.9, Price = £2,000. Figure 1 shows the changing share of preference of a supplier (Supplier 1) at different levels of volume and valence. From this analysis we can observe that there are diminishing returns for Supplier 1 at higher levels of volume and valence. We can also see that the threshold is between 50 and 100 for volume and between 3.9 and 4.1 for valence. This is in line with the text-based comments from our respondents. For example, a respondent mentioned “I assumed that after 100 ratings the average rating wouldn't change significantly so I looked for products with 100+ ratings.” Another described their decision-making criterion as “I tried to find a balance between sufficient reviews (preferably more than 50) and a sufficient rating (where possible above or close to 4.0) as this would indicate a generally good performance experience.” The regression analyses provide further insights into these findings.

Insert table 3 & figure 1 here

5.2 Hypothesis testing: Regression analyses

CBC designs enables us to create utility functions for each respondent, that can be used to predict the chances of a respondent selecting one supplier over another, given different supplier characteristics. To understand how this preference changes with changing levels of volume, valence, and price, we created a ‘base option’ supplier with the following characteristics: Vol = 75, Val = 4.0, and Price = £ 2,000. These base option characteristics were informed by the observations from the descriptive analysis that a buyer’s threshold is likely to be between Vol: 50 and 100, Val: 3.9 and 4.1, and at the midpoint of the reference price i.e. £2,000. Then, using the utility function of each respondent, we estimated if the respondent would select an alternate, non-dominant supplier over the base option. This technique allows us to model how the probability of selecting an alternate supplier over the base option supplier changes with changing levels of the signals. Table 4 shows the results of the logistic regression model with the dependent variable as ‘Selecting the alternate supplier over the base option supplier’.

Model 1 shows that both volume (0.047, $p<0.001$) and valence (0.273, $p<0.001$) are positively and significantly correlated with the chances of the alternate supplier being selected over the base option supplier, as expected. In model 2, we introduce the quadratic terms for volume (-0.004, $p<0.001$) and valence (-0.041, $p<0.001$) to investigate if this positive effect levels off as volume and valence increase. We find that the quadratic terms have negative and significant coefficients. This indicates diminishing returns of volume and valence on the chances of the alternate supplier being selected over the base option supplier with increasing levels of volume and valence. Thus, we find evidence in support for H1.

Model 3 introduces two dummy variables for the two opposing signal combinations; specifically (i) high volume (500) with low valence (3.5) and (ii) low volume (10) with high valence (4.5). We find that in both instances, the probability of the alternate supplier being chosen over the base option is lower – but the effect is more pronounced for low volume and high valence. Furthermore, using Sawtooth's market simulator package, we ran a simulation to understand respondents' relative preference for each option: Option A (Vol = 500 and Val = 3.5) v. Option B (Vol = 10 and Val = 4.5). Our results indicate that 55.8% of our respondents would select option A over option B thus preferring an option with significantly lower valence if the volume is higher. These findings provide evidence to support H2.

Model 4 introduces deal size as a moderating variable. Contrary to our expectations, we find that a large deal size does not have any significant influence on the probability of the alternate option being selected, neither does deal size have a moderating effect on volume and valence. Thus, we do not find support for H3. In the discussion section, we propose potential explanations for this unexpected finding.

Model 5 reports the effect of price on the probability of an alternate supplier being selected over the base option supplier. We find that both volume and valence have a significant positive impact. A price point of £1,000, lower than the reference price, has a positive effect (4.536, $p<0.001$) on the chances of the alternate option being selected, but the coefficient for the higher price point of £3,000 is not significant. Furthermore, we find that both the lower and higher price points negatively moderate the impact of volume and valence on supplier selection. This indicates that respondents are most sensitive to volume and valence signals when the price is within their reference price zone. This provides supporting evidence for H4.

Insert table 4 here

5.3 Further analysis to assess trade-offs for new suppliers

Sensitivity analysis using CBC experimental data enables us to understand trade-offs for suppliers with specific profiles in different competitive settings. While this analysis can be done for various combinations, studying the prospects of a new entrant (Supplier 1) that has yet to build up their online reputation is useful as prior research indicates that new suppliers often find it difficult to establish themselves in B2B markets (Rottenburger and Kaufmann, 2019). Therefore, we study the share of preference of a new entrant with changes in its volume, valence, and price vis-à-vis an established competitor (Supplier 2). As the supplier 2 is likely to have higher volume and a price within the reference price zone, we decided to run the sensitivity analysis with competitors at different levels of valence. Figure 2 (a) (b) and (c) shows the sensitivity analysis of new supplier (Supplier 1) with characteristics Vol = 10, Val = 3.9, Price = £ 2,000, against three different established competitors with different levels of valence. From figure 2(a) we can once again observe the diminishing returns for volume. In figure 2(b) we can clearly observe the threshold effect between 3.9 and 4.1 for suppliers 2A and 2B, but against the strongest supplier 2C, which has a valence of 4.1, we do not observe a threshold – thus further indicating that valence is interpreted in the context of volume. Finally, from figure 2(c), we find that buyers avoid high price options and tend to prefer lower priced options regardless of the social media signals. This was also echoed in the respondents' comments. For instance, one respondent started explaining their logic as "Having ruled out any over my budget, which I set at the top end of the typical price range…". Another summarised their price logic as "I aimed to stick within the price range, for the best rating with the largest number of ratings".

Insert figure 2 (a) (b) (c) here

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6. Discussion

Research indicates that to overcome some of the information asymmetry in B2B markets, buyers are likely to rely on signals that are either generated by the supplier – intentional signals, or by the market – unintentional signals, to shortlist and engage with suppliers in online B2B markets (Lanzolla and Frankort, 2016). As many suppliers provide the same intentional signals, studying how buyers are influenced by unintentional signals such as those generated by social media feedback presents both theoretical and practical relevance.

6.1 Implications for research

We believe our research opens new lines of inquiry in behavioural operations management research, especially regarding the mechanisms by which buyers interpret social media signals and how these ultimately influence their choice (Tokar, 2010).

<u>Buyer's interpretation of social media signals and its impact:</u> Research on signalling in B2C as well as B2B markets has predominantly considered the use of intentional signals (such as certifications) – taking the seller's perspective as a signaller and not the perspective of the buyer. Our research aims to address this gap. We explore the trade-offs that buyers have to consider when choosing between different suppliers that offer different configurations of social media signals. Furthermore, we take into account how the interpretation of these signals changes in different pricing contexts (Connelly et al., 2011).

First, taking the buyer's perspective, we show that unintended signals from social media ratings influence a buyer's choices. But unlike some objective intentional signals such as certifications, there is heterogeneity in buyers' interpretation of social media signals. Therefore, a probabilistic rather than deterministic treatment of unintentional signals would be prudent at the aggregated level (Banerjee et al., 2019). Our theoretical argument for diminishing returns for both volume and valence of social media signals provides an explanation for the possible mechanism underlying this shift in aggregated buyer behaviour. Specifically, as more individual buyers cross their idiosyncratic threshold for sufficient valence and volume, the observed aggregated effect at the macro-level would show diminishing returns. This highlights the need to further investigate judgement-confidence levels of respondents towards social media signals. Our sample of respondents seem to indicate that buyers have a threshold volume between 50 and 100 reviews and valence of 4.0/5.0.

Second, we did not find empirical evidence to show any moderating effect of the deal size on the efficacy of social media signals although profit impact, often measured by the purchasing volume, is considered an important criteria for developing effective purchasing strategies (cf. Kraljic, 1983; Luzzini et al., 2012). This seems to indicate that buyers are not sensitive to deal size and do not seem to perceive a higher importance for purchases with larger deal sizes as long as the unit price of the product is the same. This could be for two reasons. First, buyers may be selecting the supplier independently of the deal size, as the influence of the deal size comes into consideration only later in the purchasing process. Second, buyers may not consider numeric social media signals useful in assessing the strategic importance of a purchase in terms of its impact on product quality and business growth. Therefore, deal size has no significant influence on the efficacy of numeric social media signals. It is possible that text-based social media feedback in which previous buyers explain their reasons for giving a specific numeric rating would add more information on profit impact, but numeric social media signals alone do not seem to convey sufficient information on such complex matters.

Finally, research shows that buyers, like most decision-makers, are sensitive to reference points when interpreting information (Thaler 1985; Qualls and Puto 1989). Our research shows this to be the case when buyers interpret social media signals in the context of price references. We find that buyers pay more attention to social media signals when the price is within their reference price zone.

In this case, price is not diagnostic and thus buyers can focus on additional signals such as social media signals for further information. However, if price falls outside of the reference zone, it gains diagnostic value as a signal in itself and weakens the importance of social media signals. These findings further indicate possible heterogeneity in signal interpretation in the context of pricing.

<u>Trust in social media signals:</u> Trustworthiness, how it is developed and maintained, has been a concern for management researchers across disciplines (Yu et. al, 2015). The natural question that follows is to what extent buyers consider the signals generated from social media to be trustworthy. Insights from our discussion of the results combined with evidence from the B2C literature present new lines of inquiry (Babić Rosario et al., 2016). Not surprisingly, the participants mentioned that they are more likely to trust the signal as volume increases – indicating a tendency to have faith in large numbers and the "wisdom of the crowd" (Racherla et al., 2012). As a respondent commented "Star rating was important but only when there were a decent number of reviews to show that the score was a true representation" and several respondents mention " [...] the most important part of the decision was to have at least 100 ratings". This indicates that high volume can induce trust.

Threshold valence can also be a source of trust. Previous research in B2C contexts have shown that a positive first reviews can influence trust (Park et al., 2018). However, if the initial review is negative, this can potentially set in motion a downward spiral – reducing the possibility of getting more buyers and generating additional (more positive) reviews to even out that negative rating over time. Park et al. (2018) find that the effect of the first review can still be felt three years later. This implies that buyers are particularly sensitive to the valence of the first review, and increasingly they trust a larger volume of reviews. Our data shows that buyers do trade off higher volume for lower valence. As a respondent points out suppliers "[…] had to have above 4 rating. If the ratings are close, higher number of ratings are preferred, even if the rating is lower."

6.2 Implications for practice

The observations from our data reveal useful insights for practitioners that we have grouped under implications for suppliers, buyers, and market owners.

Implications for a supplier's strategy: Suppliers do not have direct control over the ratings left by buyers in the online market, however they do have some options to influence what kind of buyers they service and what price range they offer. By targeting specific buyer market segments and setting prices appropriately, they are likely to influence buyer ratings. These decisions are of particular significance in generating initial customer ratings, as our analysis suggests that suppliers can improve their chances of being selected by influencing both volume and valence of social media signals as well as price. In particular, our findings suggest that new suppliers who have yet to establish their reputation in an online B2B marketplace should focus on increasing both valence and volume of social media signals, but that increasing the volume is even more important than increasing valence. This is because many buyers seem to be aware of the "wisdom of the crowd" effect and do not trust a valence signal that is not based on a statistically meaningful number of ratings. If forced to trade off valence and volume against each other, participants in our experiment 1 would prefer a supplier with a lower valence but higher volume of ratings over one with higher valence and a lower volume of ratings (as long as valence is not "terrible", i.e., not below 3.5). From experiment 2, we learned that setting a price below the reference price diverts the focus of a buyer away from social media signals and increases the likelihood of supplier selection. Thus, in order to increase transaction volume and the volume of social media ratings, our findings suggest the new suppliers should set prices below the reference price (if feasible with their business strategy, e.g., by offering introductory promotions) until reaching a sufficient volume of social media ratings. Once a certain threshold of social media ratings has been achieved and the supplier has established a credible reputation online, they can consider raising prices to the reference price level. In our experiment, the threshold volume lies between 50 and 100 ratings.

Implications for a buyer's strategy: Feedback from previous buyers can be a useful source of additional information for supplier selection. However, if buyers are using social media feedback as an input into their decision-making calculus, they should carefully consider the role of the marketplace owner in ensuring that these ratings are genuine. Moreover, it seems that buyers already intuitively consider the valence of ratings in the context of volume. If a supplier only has few ratings, buyers tend to not give much credence to the valence of these ratings as they do not yet trust this signal. Ratings with low volume could be influenced by idiosyncratic preferences of a few buyers or even be subject to fraud. Thus, buyers should ensure that they pay attention to both signals and ensure a statistically meaningful volume of ratings before taking valence into account. Furthermore, the cycle of using social media can only function fruitfully if current buyers leave their own feedback, thus contributing to the strength of social media signals of suppliers.

<u>Implications for market owners:</u> Online B2B markets create value by bringing together large numbers of buyers and suppliers and enabling what Kaplan and Sawhney (2000) observed as marketplace liquidity: mechanisms to mediate any-to-any transaction at reduced transaction costs. The success of online markets, however, depends on the governance mechanisms enforced by the market owner aimed at ensuring fair participation in order to facilitate interactions between sellers and buyers. Better governance increases the chance to attract large numbers of customers which will also improve the market's performance. Governance mechanisms in online B2B markets can generally include (i) monitoring of participants, (ii) community building and (iii) participation in the market (Grewal et al., 2010). The effectiveness of such mechanisms, however, depends on external demand uncertainty as well as the uncertainty faced with regards to the behaviour of the market participants and the behaviour of the market owner. While community building seems to be effective under most conditions, monitoring and participation seems to be effective for reputable market owners (Grewal et al., 2010).

Given the increasing competition amongst B2B market owners, governance could become a differentiating factor. These markets often invite same or similar suppliers that claim very similar credentials, certifications, and trade assurances. Buyers therefore prefer markets that can provide additional information that is trustworthy in identifying suitable suppliers. For instance, a buyer may prefer transactions on one online market over another, regardless of the sellers' profile due to the institutional trustworthiness of one B2B market over another (Pavlou and Gefen, 2004). Therefore, one way to differentiate could be the guarantee of genuine social media feedback – especially if it can be made more relevant to the buyer. One way to increase the trustworthiness is to only allow "verified buyers" to review the supplier, so that the likelihood of fraud can be reduced. Another way is to work with a neutral third-party intermediary, such as Trustpilot or Feefo in the B2C space, to solicit and provide buyer reviews.

7. Conclusion and limitations

With the emergence of global supply chains and multi-tiered networks of suppliers, buyers face the challenge of scaling the supplier selection process without compromising efficiency. Therefore, buyers are incentivised to update their supplier-selection approach including new criteria and information that allows to improve the process – especially with regards to initial scanning in a global marketplace. In this paper, we have shown that such criteria can be social media signals, specifically volume and valance of social media feedback that is increasingly being made available on online B2B markets. This is an emergent phenomenon in supply chain management in general that is likely to have a significant impact on supplier selection practices.

Even though CBC experimental designs have advantages, they still remain a proxy for choices in real purchasing scenarios. Future research is likely to benefit by identifying different designs and contexts to test these relationships. We also have not considered the trade-offs between social media signals and many of the dominant intentional signals in our analysis. While this was done by design, there is scope to consider designs that trade-off intentional and unintentional signals. Finally, with more text-based feedback being added in B2B markets, further analysis can be done using other types of qualitative social media signals.

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Figures and tables

Table 1: Attributes and levels of the CBC experimental design

	Attribute 1	Attribute 2	Attribute 3
	Volume	Valence	Price
Level 1	10	3.5	£3,000
Level 2	25	3.7	£2,000
Level 3	50	3.9	£1,000
Level 4	100	4.1	
Level 5	250	4.3	
Level 6	500	4.5	

Table 2: Characteristics of the sample by experiment

		Experiment 1: Condition One printer *(n = 192)*	Experiment 1: Condition Fifty printers *(n = 179)*	Experiment 2: One printer and price *(n = 138)*
Purchasing experience				
1	Limited to a few times	41%	44%	38%
2	Regular	51%	49%	53%
3	Professional (< 5 years)	5%	6%	6%
4	Professional (> 5 years)	3%	2%	3%
Purchasing experience type				
1	Only physical goods	24%	22%	20%
2	Mostly physical goods	26%	27%	20%
3	Balance of physical & services	42%	42%	47%
4	Mostly services	6%	5%	10%
5	Only Services	3%	3%	2%
Age				
1	Did not say	-	-	1%
2	Less than 25y	18%	1%	20%
3	25 - 35y	49%	20%	56%
4	36 - 45y	28%	45%	17%
5	46 - 55y	4%	25%	4%
6	56 - 65y	2%	6%	-
7	Over 65y	0%	3%	1%
Education				
1	High school or less	11%	21%	10%
2	Bachelors degree (UG)	45%	37%	38%
3	Trade/ Technical/ Vocational	14%	13%	11%
4	Masters degree	23%	25%	30%
5	Professional degree	4%	3%	7%
6	Doctorate	3%	1%	4%
Gender				
1	Male	51%	54%	49%
2	Female	49%	46%	51%
3	Other (Non-binary)	0%	0%	0%

Note: Percentages rounded off and may not sum-up to 100%, less than 0.5% has been rounded off to 0% to indicate responses.

Table 3: Relative importance and part-worths for all experiments

Attributes and levels	Experiment 1: One printer condition *(n = 192)*			Experiment 1: Fifty printers condition *(n = 179)*			Experiment 2: One printer and price *(n = 138)*		
		Marginal utility	Standard Deviations		Marginal utility	Standard Deviations		Marginal utility	Standard Deviations
Volume	(52.14%)		14.72%	(52.13%)		14.99%	(33.17%)		14.83%
10	-61.55	-	16.14	-62.54	-	17.18	-58.22	-	27.40
25	-31.37	2.01	17.49	-30.06	2.17	19.09	-28.28	2.00	22.26
50	-2.84	1.14	14.89	-0.44	1.18	15.05	-3.57	0.99	19.51
100	20.90	0.47	11.32	20.87	0.43	11.77	18.34	0.44	15.92
250	32.13	0.07	13.22	30.44	0.06	12.18	30.45	0.08	18.48
500	42.73	0.04	18.68	41.72	0.05	19.03	41.28	0.04	23.80
Valence	(47.86%)		14.72%	(47.87%)		14.99%	(38.44%)		14.78%
3.5/ 5.0	-54.46	-	15.78	-54.73	-	16.44	-64.94	-	25.05
3.7/ 5.0	-30.89	11.79	16.31	-29.81	12.46	15.12	-38.09	13.43	25.56
3.9/ 5.0	-7.34	11.78	14.91	-6.86	11.48	15.45	-8.67	14.71	21.97
4.1/ 5.0	21.17	14.26	13.60	20.73	13.80	12.27	23.66	16.17	17.70
4.3/ 5.0	30.25	4.54	12.19	29.65	4.46	12.48	37.67	7.01	19.02
4.5/ 5.0	41.27	5.51	19.56	41.01	5.68	19.86	50.37	6.35	24.93
Price							(28.39%)		13.73%
£1,000							32.90	-	18.10
£2,000							19.37	-13.53	13.10
£3,000							-52.28	-71.65	24.62

Notes: Numbers in parentheses are relative importance of attributes. Part-worths are scaled for comparison across levels
Marginal utility indicates the change in part-worth per unit increase of the attribute. Unit of volume = 1, valence = 1.0, Price = £ 1

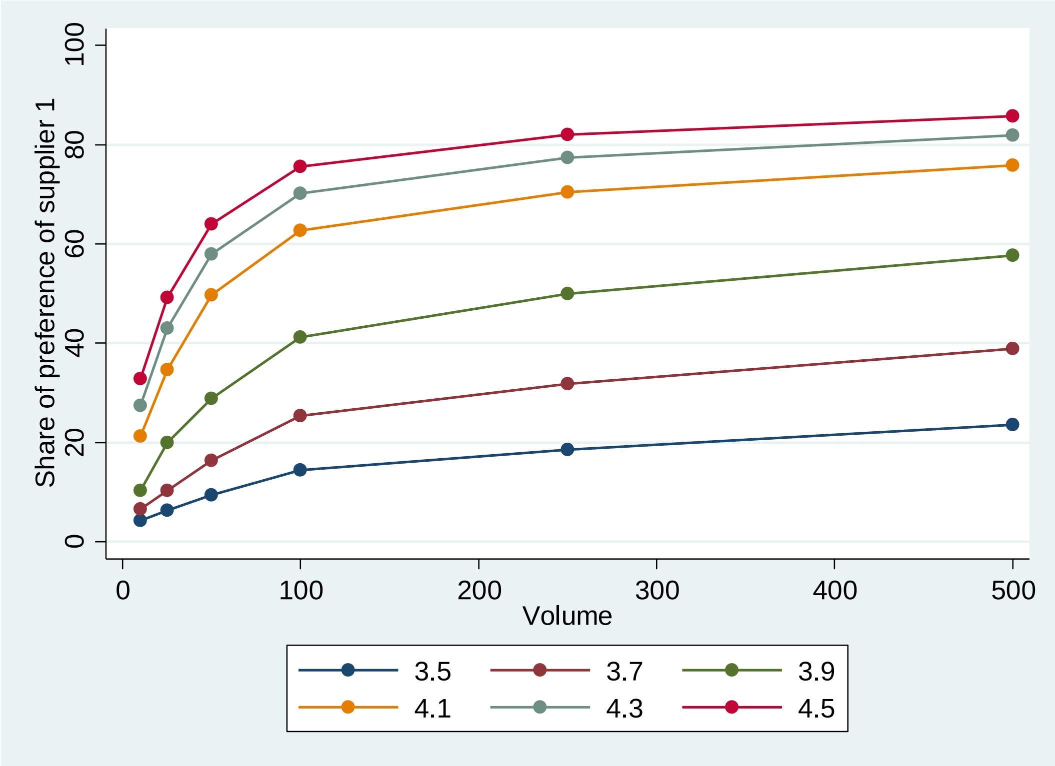
Table 4: Logit regression coefficients of selecting an alternate supplier over the base option supplier with Volume = 75, Valence = 4.0 and Price = £ 2,000

Variables	Model 1 Base	Model 2 Diminishing returns	Model 3 Opposites	Model 4 Deal Size	Model 5 Price
Volume (Unit of 10)	0.047**	0.255**	0.055**	0.047**	0.065**
	(0.002)	(0.010)	(0.002)	(0.003)	(0.003)
Valence (Unit of 0.1)	0.273**	3.780**	0.312**	0.269**	0.452**
	(0.012)	(0.266)	(0.013)	(0.016)	(0.018)
Large deal size (0/1)		-0.057	-0.055	-0.395	
		(0.059)	(0.057)	(1.017)	
Volume * Volume		-0.004**			
		(0.000)			
Valence * Valence		-0.041**			
		(0.003)			
Valence (3.5) and Volume (500)			-1.194**		
			(0.152)		
Valence (4.5) and Volume (10)			-1.976**		
			(0.158)		
Valence * Large deal size				0.008	
				(0.024)	
Volume * Large deal size				0.000	
				(0.004)	
Price (£ 1000)					4.536**
					(0.945)
Price (£ 3000)					1.445
					(1.126)
Price (£1000) * Volume					-0.013*
					(0.004)
Price (£3000) * Volume					-0.018**
					(0.004)
Price (£1000) * Valence					-0.092**
					(0.023)
Price (£3000) * Valence					-0.082*
					(0.026)
Constant	-12.164**	-88.016**	-13.642**	-11.940**	-17.895**
	(0.628)	(5.464)	(0.661)	(0.796)	(0.780)
Number of respondents	371	371	371	371	138
Likelihood ratio (LR) chi-square	698.58**	1329.06**	1002.20**	699.68**	3664.99**
Degrees of freedom	22	25	25	25	26
Pseudo R2	0.082	0.155	0.117	0.082	0.273

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

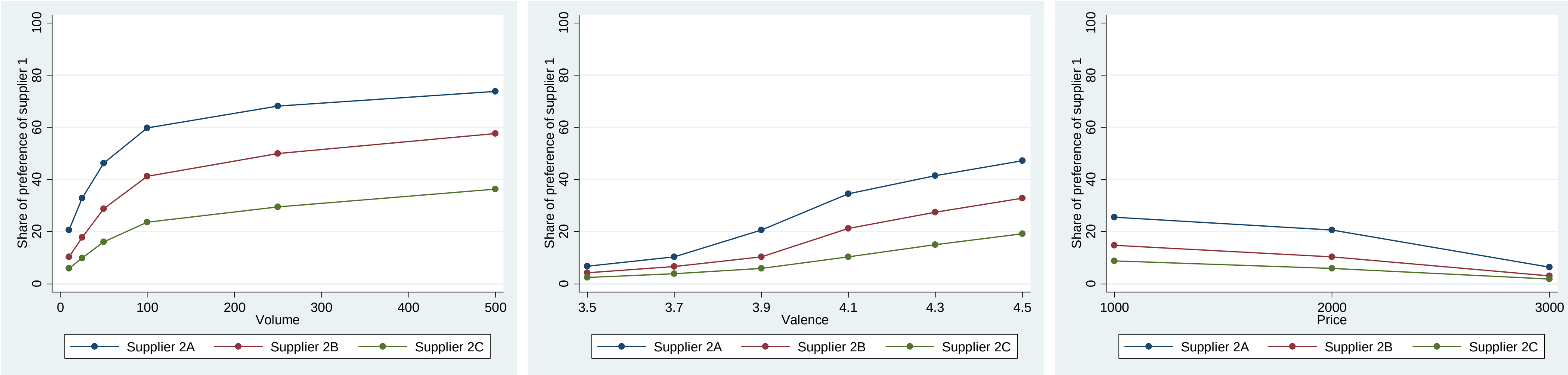
Coefficients of control variables length of purchasing experience, type of purchasing experience, age of respondent, education level, and gender were calculated but not shown. Full results with control variables are available upon request.

Figure 1: Share of preference of a supplier (supplier 1) against competitor (supplier 2) with fixed characteristics



Notes: Competitor (Supplier 2) characteristics Vol = 250, Val = 3.9, Price = £2,000

Figure 2: Share of preference of a new supplier (supplier 1) Vol = 10, Val = 3.9, and Price = £ 2,000 with (a) Changing volume (b) Changing valence (c) Changing price, against three competitors (suppliers 2A, 2B, and 2C)



Notes: Characteristics of competitors Supplier 2A Vol = 250, Val = 3.7, Price = £2,000; Supplier 2B Vol = 250, Val = 3.9, Price = £2,000; Supplier 2C Vol = 250, Val = 4.1, Price = £2,000