Information Sharing When Firms Compete for Common-Value Customers

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Abstract

Extant research suggests that the sharing of individual-level customer information benefits competing firms by allowing them to better discriminate their customers and soften the price competition. This paper shows that the information sharing may benefit competing firms even without price discrimination. Based on a common-value auction framework, the paper studies the case where two firms compete head-to-head for common-value customers who have no brand preference. Firms differ in their information about the customers' preferences on the product/service. Our model illustrates that the better informed firm would like to sell its customer data to the competitor when the data reveals more valuable customers and when the information asymmetry between firms is large. The model also examines the optimal degree of information sharing between firms. The insights from this study complement the extant literature in illustrating how information sharing allows firms to better profit from different types of customers.

Keywords: Information sharing, individual marketing, common-value auction, information economics
Introduction

Advances in information technology (IT) enable firms to collect individual consumer data by tracking customer browsing behavior, recording customer purchasing history, and prompting customers to answer questions. Firms can utilize this information to better customize products, develop targeted marketing campaign, and tailor their price offers to individual customers. Consumer data is often among the most valuable assets owned by firms. However, firms often share individual-level consumer data with each other, even when they are competing for the same consumers. For example, competing catalog marketers routinely exchange the purchase information of individual consumers to improve their customer targeting (Catalog Age 1996). Many intermediary companies specializing in customer data collection and analysis also sell their data to competing firms (Pancras and Sudhir 2007). Other information sharing practices recognized in the literature include the use of trade association (Vives 1984) and the use of common advertising agents (Villas-Boas 1994).

Extant research has examined why sharing individual-level customer information may benefit competing firms (e.g., Chen et al. 2001; Pagano and Jappelli 1993; Liu and Serfes 2006). The main insight is that sharing individual-level customer information allows firms to better segment their customers and develop different marketing strategies for different segments. Firms can better focus on their own loyal customers and avoid over-aggressive competition for other firms’ loyal customers. In this regard, the market competition can be softened, rather than intensified, by the sharing of individual-level customer information.

The above insight is based upon the premise that firms are horizontally differentiated. That is, consumers have brand preferences and the competing firms appeal to different consumer groups. Some consumers are loyal customers and only the firm they stick to can serve them and realize the customer value from them. Some consumers, on the other hand, do not have specific brand preference and any firm can serve them and realize the customer value from them (depending on the result of competition). For the second type of customer, we refer to as the common-value customer in this paper.

It is worth remarking that extant research focusing on differentiated firms left an open question: when firms can distinguish between their loyal customers and common-value customers, why do they share information on both types of customers? Ideally, if the main objective of information sharing is to discourage competing firms to over-aggressively targeting on the loyal customers of each other, firms can just selectively release the identities of their loyal customers to their competitors. On the other hand, if firms identify common-value customers, they should prevent the information of these customers from being acquired by the competitors. This can help firms maintain their advantages in competing for the common-value customers. However, most existing studies do not differentiate between the information of different types of customers when considering information sharing. Therefore, there is a need to further examine the following research question: for those common-value customers who do not have brand preference, should competing firms share their information with each other?

To examine this research question, we build a model in this paper to study the competition between two firms for common-value customers. Unlike the extant research, the firms we consider are horizontally undifferentiated in the sense that firms sell identical products (or services) and prospective customers do not have any brand preference. Firms can have information about customers. This information is not about how much the customer prefers each firm (i.e., horizontal preference), but about how much the customer prefers the identical products offered by firms (i.e., the vertical preference). In the absence of the horizontal differentiation between firms, conventional wisdom may suggest that sharing the vertical preference of customers always intensifies the competition. If a firm realizes that a specific prospective customer is a valuable customer and does not have specific brand preference, the firm should be more aggressive in competing for this customer, compared to the case where the firm does not know the customer value. In this paper, however, we show that this is not always the case. Even when the competing firms are not horizontally differentiated, the sharing of customer value information may still soften the competition in some cases. We characterize the conditions under which the information sharing may benefit firms by softening the inter-firm competition.

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1 The existing studies also find that the sharing of individual-level customer information results in more aggressive competition for the disloyal customers (e.g., Chen et al. 2001).
Another important issue is how much information should be shared among competitors. Existing studies on information sharing largely focus on a simple sharing strategy: a firm shares its entire customer database as it is. However, firms can often control the data they share with their competitors. For example, instead of sharing all individual customer data with their competitors, a firm can just share a subset of individual customer profiles and influence the information that competitors can derive from the data. In this way, the firm mitigates the inter-firm information asymmetry about customers but does not completely give up its own information advantage. In this paper, we also consider the degree of information sharing. That is, to what extent that a better informed firm would like to share its customer data with the less informed competitor.

The model we use in this paper reflects the features of common-value auction. In the model, two firms selling identical products (or services) compete in acquiring prospective customers. A prospective customer has uncertain value to firms. It can be either a valuable customer (who can generate sales revenue to firms) or an invaluable customer (who cannot generate sales revenue to firms). The two firms differ in their information about the value of a consumer. They both receive a private signal about the value of an individual consumer, but the signal of one firm (the better informed firm) is more informative than that of the other firm. Both firms spend in acquiring customers. Such expenditure can be understood as the spending on targeted advertising or targeted promotion. An individual prospective customer has no brand preference and hence buys from the firm spends more in acquisition. The paper focuses the following issues. First, when would the better informed firm like to improve the competing firm’s signal? For example, should the better firm share its data about a potential customer with the competitor to improve the latter’s knowledge? Second, to what extent the better informed firm should improve its competitor’s signal, and what influences the degree of information sharing. Third, how do firms with asymmetric information spend differently in customer acquisition and how the difference is influenced by the sharing of information?

The findings of this study are as follows. First, the paper characterizes how the firm competition is influenced by the inter-firm information asymmetry. Specifically, we find that when it is less likely for the better informed firm to receive a good signal about the prospective customer (which indicates a valuable customer) than receive a bad signal (which indicates an invaluable customer), the decrease in information asymmetry between firms always intensifies the competition. Therefore, the better informed firm has no incentive to share information in this case. However, when it is more likely for the better informed firm to receive a good signal and the information asymmetry between firms is significant enough, the decrease in information asymmetry can soften the competition. Consequently, the information sharing is feasible. We also find that the better informed firm will never voluntarily improve its competitor’s information (by giving customer data for free). However, it has an incentive to sell the information to the competitor at a price). The managerial implication of these results is that the general market conditions and the content richness of individual customer data may both improve the possibility of information sharing. In a more promising market where more customers are valuable and the better informed firm is more likely to receive signals indicating valuable customers, information sharing is more likely to occur. Also, when the customer data is richer in content so that more sales leads can be generated, the better informed firm is more likely to share the data.

Second, the model suggests that the degree of information sharing is dependent on the likelihood that the better informed firm receives a good signal about the potential customer. Specifically, if this likelihood is higher, the better informed firm would like to make both firms’ information more similar (e.g., by sharing more data). The managerial implication of this result is that the general market conditions and the content richness of individual customer information may also improve the degree of information sharing. In more promising markets where the better informed firm is more likely to receive signals about valuable customers, it may share more data with its competitors. Also, if the when the customer data is richer in content so that more sales leads can be generated, the better informed firm may share more data with its competitors.

Third, the paper also generates a counterintuitive finding that on average, both firms make comparable expenditures in customer acquisition, regardless whether they are better informed or less informed. This result suggests the important role of customer information. Better information does not help save marketing expenditure for firms. Rather, the value of information is to enable better informed firms to focus their resources on more valuable customers and harvest higher expected payoffs in competing for these customers.

The rest of the paper is organized as follows. Section 2 reviews the related literature. In section 3, we introduce the model setup. Section 4 examines the firm competition in customer acquisition. Section 5 examines potential information sharing between firms. Key managerial implications of this study are discussed in Section 6. Finally, Section 7 concludes the paper.
Related Literature

The economics and marketing research has long concerned the issue of information sharing among competing firms. Early research focused on the sharing of general demand information or cost information. For example, Vives (1984) shows that sharing demand information is favored by competing firms in price (Bertrand) competition but not in quantity (Cournot) competition. Gal-Or (1986), in contrast, finds that competing firms have incentive to share their private cost information in quantity competition, but not in price competition. Vives (1990) finds that the sharing of demand information through trade association improves the total surplus with quantity competition but decreases it with price competition.

The more recent literature on information sharing focused on the sharing of individual customer information, rather than the information about the aggregate market demand. Chen et al. (2001) examines the situation where two differentiated firms can only target individual customers imperfectly. They find that information sharing benefit firms by allowing them to better target price-sensitive customers and soften the competition on each other’s loyal customer segments. In a two-period setting, Liu and Serfes (2006) show that the exchange of information between horizontally differentiated firms helps soften competition not only by allowing firms to tailor their prices based on customer preferences in the second period, but also by mitigating the firms’ aggressiveness in market share acquisition in the first period. Pagano and Jappelli (1993) examine the credit market competition where two differentiated lenders (located in different towns) serve both local borrowers and moving borrowers. Their study shows that information sharing benefits lenders by allowing them to better price-discriminate between local borrowers and moving borrowers. Chen et al. (2002) study the case where a referral infomediary can help two differentiated firms (each with its own loyal customers) target price-sensitive customers. Their study suggests that the exclusive strategy of enrolling only one firm is optimal for the referral infomediary, since the nonexclusive enrollment strategy intensifies the price competition. The implication is that allowing competing firms to target more overlapped price-sensitive customers through the referral infomediary affect firms’ profitability in competition. In an empirical study, Pancras and Sudhir (2007) find that a customer data intermediary can profitably provide nonexclusive targeting services to firms with brand differentiation. Our paper, differing from the existing literature, focuses on how sharing of customer information arises between undifferentiated firms with no loyal customers and price discrimination.

In terms of modeling approach, this paper relates to the stream of literature on common-value auctions with asymmetric bidders. Most existing studies on common-value auctions find that better informed bidders benefit from their informational advantages, making a positive expected profit, whereas less informed bidders earn zero profit in expectation (e.g., Engelbrecht-Wiggans et al. 1983, von Thadden 2004, Hauswald and Marquez 2006). A few studies also identify the case where less informed bidders also make a positive expected profit when they receive inferior but private information (e.g., Hausch 1987, Banerjee 2005). However, these studies do not explain why in certain cases the less informed bidders’ information may lead to informational advantage, while in other cases it does not. Our paper bridges this gap and uses a unified model to capture both the case where only better informed firm has the informational advantage and the case where both the better informed and the less informed firms have informational advantages. The model generates more insights on how the competition between firms is influenced by their heterogeneous information.

Model Setup

We consider a market with two firms and a group of prospective customers. The firms compete with each other in acquiring valuable customers through individual marketing. The customers are heterogeneous in terms of their values to firms. We assume that there are two types of customers: valuable customers and invaluable customers. A valuable customer, once acquired by the firm, can generate a certain amount of revenue \( R > 0 \) for the firm during her relationship with the firm. An invaluable customer, in contrast, generates negligible revenue for the firm. We use \( V \) to denote a customer’s value to firms. Therefore, a customer value can be either \( V = R \) or \( V = 0 \) to firms. The customer relationship here can be considered as either the short-term relationship or long-term relationship. For example, if customers are one-time customers (e.g., shoppers), the customer value can be considered as the sales that a firm generates through a one-time transaction. If, on the other hand, the customers are repeated customers, then the customer value can be considered as the customer’s lifetime value to the firm (until the customer becomes inactive). We assume that there is no horizontal differentiation between the two firms in the sense that the value of any customer is the same to both firms. We use \( m_i \ (i \in \{1,2\}) \) to represent firm \( i \)'s marketing spending in acquiring a customer. Such spending
can be explained as the firm’s expenditure on target advertising or target promotion. Since firms are not horizontally differentiated, customers do not have any specific brand preference. It is assumed that each customer will be acquired by the firm who spend more in targeting this customer (e.g., sending more targeted advertisement or more individual discounts).

We assume that for firms cannot directly observe whether a specific customer is valuable or invaluable. However, they receive signals on the customer values. For example, both firms can acquire customer profile and transaction data from marketing intelligence companies, and they can analyze the data and generate sales leads from it. It is assumed that if a sales lead is generated from a customer, this customer can be either a valuable customer or an invaluable customer. If no sales lead from a customer, the firms can conclude that s/he is an invaluable customer. In this way, a sales lead imperfectly captures the sales prospect. For example, if the data shows that a specific customer is an invaluable customer for sure. We denote the expected value of a customer for firm 1, given a signal S. However, it is still likely that this customer may not be valuable. If, on the other hand, the data shows that the customer has been inactive for a long time, firms can consider this customer as an invaluable customer.2

We use S to denote the signal received by firm 1 for a customer. S has two potential values, h (i.e., a high signal) and l (i.e., a low signal). S = h means that firm 1 generates a sales lead from this customer and there is a chance that this customer is a valuable customer. S = l means that no sales lead is generated from this customer and this customer is an invaluable customer for sure. We denote the expected value of a customer for firm 1, given a signal S, as E[V | S], where S ∈ {h, l}. It is straightforward that R > E[V | h] > E[V | l] = 0. We use Pr(h) and Pr(l) to denote the probabilities that firm 1 receives S = h and S = l, respectively.

We assume that firm 2 also receives a signal Š. Š has two potential values, ŝ (i.e., a high signal) and ī (i.e., a low signal). Compared with firm 1’s signal S, Š is less precise in indicating the customer value. Specifically, we use Pr(ĥ | Š) and Pr(ī | Š) to denote the probabilities of Š = ī and Š = ī respectively, conditional on Š. Pr(ĥ | Š) and Pr(ī | Š) are defined as the follows,

\[ \text{Pr}(\tilde{h} | h) = \frac{1+z}{2} \text{, Pr}(\tilde{i} | h) = \frac{1-z}{2}. \]

z ∈ [0, 1] is the relative precision of the signal Š. It captures the precision of the signal Š relative to the signal S. If z > 0, when S = h, it is more likely that Š = ī. In other words, when firm 1 receives a high signal, it is more likely that firm 2 also receives a high signal. Similarly, when firm 1 receives a low signal S = l, it is more likely that firm 2 also receives a low signal Š = ī. However, when 0 < z < 1, the signal Š is not as precise as S (as shown below). If z = 1, the signal Š is as precise as S. When z = 0, the signal Š contains no useful information.

Given the signal Š, the expected value of a customer for firm 2 can be represented by

\[ E[V | Š] = P(h | Š)E[V | h] + P(l | Š)E[V | l], \]

where P(h | Š) and P(l | Š) are posterior probabilities of S = h and S = l respectively, given the signal Š ∈ {ĥ, ī}. Using the Bayes’ rule, we have

\[ P(h | Š) = \frac{\text{Pr}(\tilde{h} | h) \text{Pr}(h)}{\text{Pr}(\tilde{h} | h) \text{Pr}(h) + \text{Pr}(\tilde{i} | h) \text{Pr}(l)} \text{, and } P(l | Š) = \frac{\text{Pr}(\tilde{i} | l) \text{Pr}(l)}{\text{Pr}(\tilde{h} | h) \text{Pr}(h) + \text{Pr}(\tilde{i} | l) \text{Pr}(l)}. \]

With some algebra (more details in the Appendix3), we can confirm the following relationships.

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2 Although customers with no sales leads may still be valuable customer with little chance, we simplify the analysis by considering that these customers are not operationally worthwhile to serve.

3 To conserve space, all the proofs are not included here, but are in Appendix which is available from the authors upon request.
Remark: $E[V \mid I] \leq E[V \mid \bar{h}] \leq E[V \mid h] \leq E[V \mid h]$. The Remark suggests that compared with a high signal $S = h$, a high signal $\tilde{S} = \tilde{h}$ is less likely to indicate a valuable customer (since the conditional expected value of customer on $\tilde{S} = \tilde{h}$ is lower than that on $S = h$). Similarly, compared with a low signal $S = l$, a low signal $\tilde{S} = \tilde{l}$ is less likely to indicate an invaluable customer. In this regard, the signal $\tilde{S}$ is less precise than the signal $S$ in indicating the type of customer. In the model, it is assumed that the distributions of the signals (i.e., the probabilities $Pr(h)$, $Pr(l)$, $Pr(\tilde{h} \mid S)$ and $Pr(\tilde{l} \mid S)$) are known by both firms.

The timing of the events in the model is as follows. First, both firms receive their signals. That is, firm 1 receives $S$, and firm 2 receives $\tilde{S}$. Second, both firms simultaneously decide their spending in customer acquisition. Finally, the customer is acquired by the firm spending more. The value of the customer is realized for the firm.

Firm Competition

We first characterize the Bayesian Equilibrium of the customer acquisition competition between firms. In the competition, for each prospective customer, firm $i$ chooses its spending, $m_i$, to maximize its expected payoff from this customer, denoted by $\pi_i, i = 1, 2$. The competition on each prospective customer between firms can be characterized by a common-value all-pay auction. The number of customers becomes irrelevant and therefore, from now on, we focus on the firm competition on a single representative customer.

In this case, there is no pure-strategy equilibrium for this game. The rationale is that if firm 2 spends a fixed amount $m_2$, firm 1’s best-response is always to spend more than $m_2$ if $E[V \mid S] > m_2$. As a result, firm 2 can only acquire a customer when $E[V \mid S] \leq m_2$, which leaves a non-positive expected payoff for firm 2. This is a typical case of the Winner’s Curse. Therefore, firm 2 has to randomize its spending. The only equilibrium is a mixed-strategy equilibrium. (The proof of non-existence of pure-strategy equilibrium is in the Appendix.)

Let $G_i(m \mid S) = Pr(m_i \leq m \mid S)$ denote the equilibrium cumulative distribution functions (CDF) of firm 1’s spending, conditional on firm 1’s signal $S$. Let $G_2(m \mid \tilde{S}) = Pr(m_2 \leq m \mid \tilde{S})$ denote the equilibrium CDF of firm 2’s spending, conditional on firm 2’s signal $\tilde{S}$. Firm 1’s expected payoff when spending $m_1$, conditional on its signal $S$, can be represented as

$$\pi_1(m_1 \mid S) = Pr(\tilde{h} \mid S)G_1(m_1 \mid \tilde{h})E[V \mid S] + Pr(\tilde{l} \mid S)G_1(m_1 \mid \tilde{l})E[V \mid S] - m_1. \quad (2)$$

The first term in the right-hand side (RHS) of Exp. (2) is firm 1’s expected revenue when firm 2 receives a high signal $\tilde{S} = \tilde{h}$. The second term is firm 1’s expected revenue when firm 2 receives a low signal $\tilde{S} = \tilde{l}$. Similarly, firm 2’s expected payoff by spending $m_2$, conditional on its signal $\tilde{S}$, can be represented as

$$\pi_2(m_2 \mid \tilde{S}) = Pr(h \mid \tilde{S})G_1(m_2 \mid h)E[V \mid h] + Pr(l \mid \tilde{S})G_1(m_2 \mid l)E[V \mid l] - m_2. \quad (3)$$

The first term in the RHS of Exp. (3) is firm 2’s expected revenue when firm 1 receives a high signal $S = h$. The second term is firm 2’s expected revenue when firm 1 receives a low signal $S = l$.

In equilibrium, firms compete in different patterns depending on the distribution of signal $S$. Proposition 1 characterizes the firms’ equilibrium competition strategies when $Pr(h) \leq Pr(l)$, i.e., when it is (weakly) less likely for firm 1 to receive $S = h$ than to receive $S = l$.

Proposition 1. If $Pr(h) \leq Pr(l)$, firms’ equilibrium spending in customer acquisition is as follows.

1. When firm 1 receives $S = l$, it spends zero (i.e., no spending);
2. When firm 2 receives $\tilde{S} = \tilde{l}$, it spends zero.
When firm 1 receives \( S = h \), it randomizes its spending and the CDF of its spending is
\[
G_1(m|h) = \frac{m}{\Pr(h|h)E[V|h]}, \quad \text{where} \ m \in [0, E[V|h]).
\]

When firm 2 receives \( S = \tilde{h} \), it randomizes its spending and the CDF of its spending is
\[
G_2(m|\tilde{h}) = \frac{\Pr(I|\tilde{h}) - \Pr(I|h)}{\Pr(h|h)E[V|h]}E[V|h] + m, \quad \text{where} \ m \in [0, E[V|h]).
\]

To better illustrate how firms compete based on their signals, Figure 1(I) shows the support of firms’ randomized spending when \( \Pr(h) \leq \Pr(l) \). As Proposition 1 shows, when firm 1 receives a low signal \( S = l \), it expects that the value of the customer is \( E[V|l] = 0 \). Consequently, firm 1 does not spend in acquiring this customer when \( S = l \), and its expected payoff in this case is zero. When firm 1 receives a high signal \( S = h \), the expected customer value for firm 1 is \( E[V|h] > \max\{E[V|\tilde{h}], E[V|\tilde{l}]\} \). Firm 1 therefore has more incentive than firm 2 to win this customer. In equilibrium, firm 1 randomizes its customer acquisition spending in such a way that firm 2 earns a zero expected payoff (e.g., Engelbrecht-Wiggans et al. 1983; von Thadden 2004; Hauswald and Marquez 2006).

For firm 2, when it receives a low signal \( \tilde{S} = \tilde{l} \), it expects that the customer value is \( E[V|\tilde{l}] > 0 \). However, we find that firm 2’s equilibrium strategy of customer acquisition in this case is not to spend. It then receives zero expected payoff. Firm 2 gives up the competition because it cannot observe firm 1’s signal. When firm 1 receives \( S = l \), firm 2 can win the customer for sure if it spends a positive amount in customer acquisition. However, in this case, firm 2 will acquire an invaluable customer who cannot generate a positive expected revenue to cover firm 2’s acquisition expenditure. In other words, firm 2 is worse off by winning the customer. This is a typical case of Winner’s Curse. On the other hand, when firm 1 receives a high signal \( S = h \), firm 1 will compete aggressively for this customer. Firm 1’s superior information about the customer value provides it an advantage in the competition. In equilibrium, firm 1 randomizes its customer acquisition spending in such a way that firm 2 cannot earn a positive
expected payoff. In this case, even if firm 2 competes, it cannot do better than giving up the competition. Therefore, firm 2 does not spend when it receives \( \hat{S} = \hat{t} \).

When firm 2 receives a high signal \( \tilde{S} = \tilde{h} \), it expects that the customer is valuable enough for it to compete with firm 1. Therefore, firm 2 also randomizes its spending to acquire this customer. Since \( E[V | \hat{h}] \) is the highest expected value if firm 2 receives a signal \( \tilde{S} = \tilde{h} \), firm 2 will never spend more than \( E[V | \hat{h}] \). Therefore, the upper bound of their spending distributions is \( E[V | \hat{h}] \) (e.g., Narasimhan 1988). In the mixed-strategy equilibrium, firm 1 and firm 2 randomize their spending over the same support \( [0, E[V | \hat{h}]] \). The proof of the equilibrium spending distribution functions \( G_1(m | h) \) and \( G_2(m | \tilde{h}) \) is in Appendix. In equilibrium, firm 2’s expected payoff is always zero no matter what signal it receives. However, firm 1’s expected payoff is \( E[V | \hat{h}] - E[V | \tilde{h}] \geq 0 \) when it receives \( S = h \) and 0 when it receives \( S = l \).

Proposition 2 characterizes the firms’ equilibrium competition strategies when \( \Pr(h) > \Pr(l) \), i.e., when it is more likely for firm 1 to receive \( S = h \) than to receive \( S = l \).

**Proposition 2.** If \( \Pr(h) > \Pr(l) \), firms’ equilibrium spending in customer acquisition is as follows.

1. When firm 1 receives \( S = l \), it spends zero (i.e., no spending);
2. When firm 2 receives \( \tilde{S} = \tilde{t} \), it randomizes its spending, and the CDF of its spending is
   \[
   G_2(m | \tilde{t}) = \begin{cases} 
   \frac{\Pr(\tilde{t} | h) - \Pr(h | \tilde{t})}{\Pr(\tilde{t} | h)} E[V | h] + m, & m \in [0, \hat{m}] \\
   \frac{\Pr(\tilde{t} | h) E[V | h]}{\Pr(h | \tilde{t}) E[V | h]} & m \in [\hat{m}, \hat{m}] 
   \end{cases}
   \]
3. When firm 1 receives \( S = h \), it randomizes its spending, and the CDF of its spending is
   \[
   G_1(m | h) = \begin{cases} 
   \frac{\Pr(\tilde{t} | h) E[V | h]}{\Pr(h | \tilde{t}) E[V | h]} & m \in [0, \hat{m}] \\
   \frac{\Pr(h | \tilde{t}) - \Pr(\tilde{t} | h) \Pr(h | \tilde{t})}{\Pr(h | \tilde{t}) E[V | h]} E[V | h] + m, & m \in [\hat{m}, \hat{m}] 
   \end{cases}
   \]
4. When firm 2 receives \( \tilde{S} = \tilde{h} \), it randomizes its spending, and the CDF of its spending is
   \[
   G_2(m | \tilde{h}) = \frac{\Pr(\tilde{t} | h) - \Pr(\tilde{t} | \tilde{h})}{\Pr(\tilde{t} | h) E[V | h]} E[V | h] + m, \quad m \in [\hat{m}, \hat{m}].
   \]

The cutoff levels \( \hat{m} \) and \( \hat{m} \) are derived in the Appendix.

The equilibrium in Proposition 2 can be explained as follows. When firm 1 receives \( S = l \), it expects that the value of the customer is 0 and does not spend in customer acquisition. When firm 1 receives \( S = h \), we find that firm 1 competes less aggressively than it does in the case where \( \Pr(h) \leq \Pr(l) \). Firm 1’s less aggressive competition means that it assigns more probabilities to spending less. To see why firm 1 competes less aggressively, let us examine the condition \( \Pr(h) > \Pr(l) \). This condition is equivalent to the following condition

\[
\Pr(\tilde{t} | h) E[V | h] > E[V | h] - E[V | \tilde{h}].
\]

Exp. (4) compares the expected payoffs of two competitive strategies for firm 1 when firm 1 receives \( S = h \). The RHS is firm 1’s payoff if it spends \( m_1 = E[V | \tilde{h}] \) and acquires the customer for sure. Note that when firm 1 receives \( S = h \), it expects that the customer value is \( E[V | \tilde{h}] \). Since the highest customer value that firm 2 can
expect is $E[V | \tilde{h}]$ (i.e., the customer value that firm 2 expects when it receives a high signal $\tilde{S} = \tilde{h}$), firm 2 never spend more than $E[V | \tilde{h}]$. Thus, firm 1’s expected payoff when it spends $m_1 = E[V | \tilde{h}]$ is $E[V | \tilde{h}] - E[V | \tilde{h}]$. However, firm 1 can also choose not to beat firm 2 all the time. Consider the case where firm 2 follows the strategy in Proposition 1—firm 2 does not spend when it receives $\tilde{S} = \tilde{l}$. If firm 1 spends slightly above 0, it can win the customer only when firm 2 receives $\tilde{S} = \tilde{l}$. The left-hand side (LHS) of Exp. (4) is firm 1’s expected payoff if it follows this strategy.

Exp. (4) implies that when $\Pr(h) > \Pr(l)$, firm 1 no longer finds it optimal to beat firm 2 all the time. Instead, firm 1 would rather bet on the chance that firm 2 receives $\tilde{S} = \tilde{l}$ and only wins in that case. Therefore, firm 1 competes less aggressively when it receives $S = h$. Another feature of the equilibrium indicating firm 1’s less aggressiveness is the upper bound of firm 1’s randomized spending. The upper bound in Proposition 2 is $\tilde{m}$, which is lower than the upper bound $E[V | \tilde{h}]$ in Proposition 1.

Note that a key difference between Proposition 1 and Proposition 2 is that in Proposition 2, firm 2 also randomizes its spending when it receives $\tilde{S} = \tilde{l}$. The reason is that compared to the case where $\Pr(h) \leq \Pr(l)$, firm 1 competes less aggressively when $\Pr(h) > \Pr(l)$. This also changes firm 2’s competition strategy. When firm 2 receives a signal $\tilde{S} = \tilde{l}$, it no longer finds it optimal to spend zero. Instead, firm 2 becomes opportunistic and would like to spend in customer acquisition, hoping it can beat the less aggressive firm 1 which receives $S = h$. That is why firm 2 randomizes its spending over the support $[0, \tilde{m}]$, where $\tilde{m}$ is the highest amount that firm 2 would like to spend when it receives $\tilde{S} = \tilde{l}$. In other words, firm 1’s less aggressiveness motivates firm 2 to compete more aggressively when receiving $\tilde{S} = \tilde{l}$. In equilibrium, however, the firm 2 receiving $\tilde{S} = \tilde{l}$ still earns zero expected payoff in competition. This is because for the firm 1 receiving $S = h$, even though it becomes less aggressive (compared to the case of $\Pr(h) \leq \Pr(l)$), it still has more incentive than the firm 2 receiving $\tilde{S} = \tilde{l}$ to win the customer. Therefore, in the mixed-strategy equilibrium, the firm 1 receiving $S = h$ randomizes its spending in such a way that the firm 2 receiving $\tilde{S} = \tilde{l}$ cannot gain a positive expected payoff. When firm 2 receives a $\tilde{S} = \tilde{h}$, it then randomizes its spending $m_2$ over $[\tilde{m}, \tilde{m}]$. Note that $\tilde{m} < E[V | \tilde{h}]$ when $\Pr(h) > \Pr(l)$. Therefore, firm 2 makes a positive profit, $E[V | \tilde{h}] - \tilde{m}$, when it receives a high signal $\tilde{S} = \tilde{h}$.

Firm 1, when receiving $S = h$, competes with firm 2 both when firm 2 receives $\tilde{S} = \tilde{l}$ and when firm 2 receives $\tilde{S} = \tilde{h}$. Therefore, firm 1’s spending distribution function $G_1(m | h)$ is kinked at $\tilde{m}$. The range $[\tilde{m}, \tilde{m}]$ is firm 1’s support for competition with the firm 2 which receives $\tilde{S} = \tilde{h}$, and the range $[0, \tilde{m}]$ is firm 1’s support for competition with the firm 2 which receives $\tilde{S} = \tilde{l}$. Since $\tilde{m} < E[V | \tilde{h}]$, firm 1 makes a positive profit, $E[V | \tilde{h}] - \tilde{m}$, when it receives a signal $\tilde{S} = \tilde{h}$.The equilibrium spending distributions $G_1(m | h)$, $G_2(m | \tilde{h})$, and $G_2(m | \tilde{I})$ are derived in the Appendix.

Proposition 3 compares the two firms’ equilibrium spending in customer acquisition.

**Proposition 3.** (1) Both firms’ expected expenditures in customer acquisition are equal, i.e., $E[m_1] = E[m_2]$;

(2) If $\Pr(h) \leq \Pr(l)$, when firms receive high signals, firm 1 is more aggressive than firm 2 in customer acquisition, i.e., $E[m_1 | h] > E[m_2 | \tilde{h}]$; (Note that they do not spend when they receive low signals.)

(3) If $\Pr(h) > \Pr(l)$, firm 2 is more (less) aggressive in customer acquisition than firm 1 when $\tilde{S} = \tilde{h}$ ($\tilde{S} = \tilde{l}$), i.e., $E[m_2 | \tilde{I}] < E[m_1 | h] < E[m_2 | \tilde{h}]$. (Note that firm 1 does not spend when it receives a low signal.
Proposition 3.1 presents an interesting result about the firms’ expected expenditures. That is, firms’ expected expenditures in customer acquisition are the same despite their information difference. The better informed firm and the less informed firm spend the same on average. To better explain this result, Proposition 3.2 and Proposition 3.3 further characterize firms’ expenditure in the cases of \( \text{Pr}(h) \leq \text{Pr}(l) \) and \( \text{Pr}(h) > \text{Pr}(l) \), respectively. When \( \text{Pr}(h) \leq \text{Pr}(l) \), we have \( \text{Pr}(h) \leq \text{Pr}(\tilde{h}) \). That is, firm 1 is less likely than firm 2 to receive a high signal. In this case, the firm 1 receiving \( S = h \) spends more (in expectation) than the firm 2 receiving \( \tilde{S} = \tilde{h} \). This result implies that the better information allows firm 1 to focuses its spending more specifically on a few prospects it identifies.

When \( \text{Pr}(h) > \text{Pr}(l) \), we have \( \text{Pr}(h) > \text{Pr}(\tilde{h}) \). That is, firm 1 is more likely than firm 2 to receive a high signal. In this case, firm 2 spends in customer acquisition both when it receives \( \tilde{S} = \tilde{h} \) and when it receives \( \tilde{S} = \tilde{l} \). Firm 1, however, only spends when it receives \( S = h \). When firm 1 spends, its average spending is higher than firm 2’s expected spending when firm 2 receives \( \tilde{S} = \tilde{l} \), but lower than firm 2’s expected spending when firm 2 receives \( \tilde{S} = \tilde{h} \). In other words, firm 2 plays diversified strategies. It bets more on its high signal and less on its low signal. However, on average, the two firms’ expected expenditures are still comparable to each other. This result is also consistent with the finding in Proposition 2 that when \( \text{Pr}(h) > \text{Pr}(l) \), firm 1 competes less aggressively by betting on the chance that firm 2 receives \( \tilde{S} = \tilde{l} \).

The results of Proposition 3 generate an interesting implication about the role of information in competition. The existing literature focuses more on how competing firms’ average competition aggressiveness is difference due to the information asymmetry (e.g., Chen et al. 2001). Our results suggest that information asymmetry may not necessarily lead to the difference in competing firms’ average aggressiveness. However, superior information helps firms better focus their marketing resources on the sales prospects. Proposition 4 summarizes the expected payoffs of firms.

**Proposition 4.** When information asymmetry exists, i.e., \( z < 1 \),

1. When \( \text{Pr}(h) \leq \text{Pr}(l) \), firm 1 makes a positive expected payoff and firm 2 makes zero expected payoff;
2. When \( \text{Pr}(h) > \text{Pr}(l) \), both firms make positive expected payoff;
3. Firm 1’s expected payoff is higher than firm 2’s expected payoff.

Proposition 4 illustrates that when \( \text{Pr}(h) \leq \text{Pr}(l) \), only the better informed firm, i.e., firm 1, earns an information rent in the competition with firm 2. This finding is consistent with the existing literature on common-value auction with asymmetric bidder information (e.g., Engelbrecht-Wiggans et al. 1983, von Thadden, 2004, Hauswald and Marquez, 2006). However, when \( \text{Pr}(h) > \text{Pr}(l) \), both firms earn positive expected payoffs in equilibrium. In other words, both firms earn information rents in this case. This is due to the fact that although firm 1 is a better informed, it cannot directly observe firm 2’s signal. Therefore, even though firm 2’s private information is not as good as firm 1’s in revealing the customer value, it still provides firm 2 certain advantage in competition. Existing studies have recognized the possibility that less informed bidders with private information may also earn positive information rents (e.g., Hausch 1987, Banerjee 2005). However, this conclusion is drawn under restrictive assumptions. In addition, the case where only better informed bidders earn information rent and the case where both the better informed bidders and the less informed bidders earn information rents have been examined separately. Therefore, it is not clear when the informational advantage of the less informed bidder arises and when it does not. The study, in contrast, uses an integrated model to capture both of these cases and illustrate the conditions under which they arise. As Proposition 4 indicates, whether or not the less informed firm can have a positive rent is dependent on the distribution of the better informed firm’s signal, i.e., the signal \( S \).

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4 For example, Hausch (1987) assumes that bidders always have the same probabilities of receiving a good (bad) signal conditional on its competitor’s receiving a bad (good) signal. Banerjee (2005) assumes that bidders never bid when receiving bad signals.
Information Sharing

The preceding section characterizes the firm competition in the presence of information asymmetry between firms about the customer value. In this section, we examine how the change in the information asymmetry between firms influences the competition. This analysis helps examine the key research question, i.e., whether the better informed firm (i.e., firm 1) has an incentive to share information with the less informed firm (i.e., firm 2).

The information sharing is modeled as the increase of relative precision $z$. Note that when $z$ increases, the signals received by the two firms become more similar. In other words, the increase of $z$ reduces the level of information asymmetry between firms. It is worth remarking that in this study, the inter-firm information sharing is not modeled as the sharing of the firms’ exact signal values. In other words, the signals of both firms are still private signals. However, information sharing allows firms to derive more similar signals from the same customer. This modeling assumption reflects the sharing practices in the real world. In most cases, firms share with each other the customer data rather than the specific managerial insights generated from this data. Using the same customer data, different firms may draw different conclusions about customers. In addition, this modeling approach allows us to capture the degree of information sharing. For example, a firm may not share all details of customer records with its competitors. It may just share a few fields of customer records, and the insights that competitors develop from the partial data can be different from that developed from the complete data. In our model, this degree of information sharing is modeled as firm 1’s choice of $z$, the relative precision of firm 2’s signal to firm 1’s signal.

Following the existing literature (e.g., Chen et al. 2001), we consider firm 1’s incentives for both voluntary sharing and paid sharing. In voluntary sharing, firm 1 improves the relative precision $z$ of firm 2’s signal for free (e.g., give away its data to firm 2). In paid sharing, in contrast, firm 2 needs to make a payment to firm 1 as a return for the improvement of its signal quality.

To examine firm 1’s incentive to share information, we first examine how the change of the relative precision $z$ influences the firms’ expected spending in competition.

**Proposition 5.** (1) When $\Pr(h) \leq \Pr(l)$, firms’ expected expenditures $E[m_1]$, $E[m_2]$, $E[m_1 | h]$ and $E[m_2 | h]$ are all increasing in $z$;
(2) When $\Pr(h) > \Pr(l)$,

(2.1) Both firms’ expected expenditures (i.e., $E[m_1]$ and $E[m_2]$) are decreasing in $z$ when

$z \in [0, \max \{0, z_1\}]$ and increasing in $z$ when $z \in (\max \{0, z_1\}, 1]$;

(2.2) $E[m_1 | h]$ is decreasing in $z$ when $z \in [0, \max \{0, z_1\}]$ and increasing in $z$ when

$z \in (\max \{0, z_1\}, 1]$;

(2.3) $E[m_2 | h]$ is decreasing in $z$ when $z \in [0, \max \{0, z_2\}]$ and increasing in $z$ when

$z \in (\max \{0, z_2\}, 1]$;

(2.4) $E[m_2 | l]$ is always decreasing in $z$,

where $z_2 > z_1$. The cutoff points $z_1$ and $z_2$ are derived in the Appendix.

As Proposition 5 illustrates, when $\Pr(h) \leq \Pr(l)$, the increase of $z$ intensifies the firm competition in customer acquisition. In this case, firms do not spend when they receive low signals, but randomize their spending when they receive high signals. Proposition 5.1 shows that firms’ expected expenditures, $E[m_1]$, $E[m_2]$, $E[m_1 | h]$ and $E[m_2 | h]$, are all increasing in $z$. In other words, when $z$ increases and firms’ signals become more similar, they compete more aggressively by spending more in acquiring a customer.

Proposition 5.2 shows that when $\Pr(h) > \Pr(l)$, the increase of $z$ has mixed effects on the firm competition. When $z$ is relatively small, the increase of $z$ softens the competition since firms’ average spendings are decreasing in $z$. When $z$ is relatively large, the increase of $z$ intensifies the competition since firms’ average spendings are increasing in $z$.
When \( \Pr(h) > \Pr(l) \), firm 2 spends in customer acquisition both when it receives \( \hat{S} = \tilde{l} \) and when it receives \( \hat{S} = \tilde{i} \). When it receives \( \hat{S} = \tilde{i} \), firm 2 randomizes its spending to compete with the firm 1 receiving \( S = h \). Note that firm 2 does not know whether firm 1 receives \( S = h \) or not. If the relative precision \( z \) is higher, firm 2’s information is more precise. When firm 2 receives \( \hat{S} = \tilde{l} \), it is more confident that firm 1 also receives a low signal \( S = l \). As a consequent, firm 2 will be less opportunistic and less willing to compete. That is why its expected spending \( E[ m_2 | \tilde{l} ] \) is always decreasing in \( z \).

When \( z \) is small, the less aggressiveness of firm 2 when it receives \( \hat{S} = \tilde{l} \) also motivates firm 1 to compete less aggressively. That is why firm 1’s expected spending \( E[ m_1 | h ] \) is decreasing in \( z \) when \( z \) is small. In this case, when firm 1 receives \( S = h \), it is then concerned less about the competitive threat from the firm 2 receiving \( \hat{S} = \tilde{i} \). Moreover, the less aggressiveness of firm 1 also motivates firm 2 to compete less aggressively when it receives \( \hat{S} = \tilde{h} \). That is why firm 2’s expected spending \( E[ m_2 | \tilde{h} ] \) is decreasing in \( z \) when \( z \) is small.

When \( z \) is large, the increase of \( z \) drives both firms to compete more aggressively when they receive high signals. The increase of \( z \) makes firms’ information more similar. When firm 1 receives a high signal \( S = h \), it is more likely that firm 2 also receives a high signal \( \hat{S} = \tilde{h} \). Therefore, although firm 1 knows that firm 2 is less aggressive if it receives \( \hat{S} = \tilde{l} \), firm 1 still has to compete aggressively (by increasing its expected spending \( E[ m_1 | \tilde{h} ] \)) to prepare for the more likely case that firm 2 receives \( \hat{S} = \tilde{h} \). Similarly, when firm 2 receives \( \hat{S} = \tilde{h} \), it expects that firm 1 is likely to receive \( S = h \). Therefore, firm 2 competes aggressively by increasing its expected spending \( E[ m_2 | \tilde{h} ] \). This is also why both firms’ average spendings \( E[ m_1 ] \) and \( E[ m_2 ] \) are eventually increasing in \( z \) when \( z \) is large.

Proposition 6 illustrates the impact of \( z \) on the expected payoffs of firms.

**Proposition 6.** Firm 1’s expected payoff is always decreasing in \( z \).

1. When \( \Pr(h) > \Pr(l) \), firm 2’s expected payoff is first increasing in \( z \) when \( z \in [0, z_3] \), and then decreasing in \( z \) when \( z \in (z_3, 1] \), where \( z_3 = \frac{1 - \gamma (1 - \gamma)}{2 \gamma - 1} \). (Note that when \( \Pr(h) \leq \Pr(l) \), firm 2’s expected payoff is always zero.)

When \( \Pr(h) \leq \Pr(l) \), only firm 1 has an information rent and its expected payoff is positive. Firm 2 makes a zero expected payoff, as Proposition 4 shows. The increase of \( z \) leads to more similar information between firms. As Proposition 5 shows, both firms spend more in customer acquisition, eroding firm 1’s information rent. That is why firm 1’s expected payoff is decreasing in \( z \) when \( \Pr(h) \leq \Pr(l) \).

When \( \Pr(h) > \Pr(l) \), both firms have information rents and make positive expected payoffs as Proposition 4 shows. Proposition 5 indicates that when \( z \) is small, the increase in \( z \) softens the firm competition and drives firms to spend less. However, we find that firm 1 does not benefit from the softened competition. Its expected payoff is always decreasing in \( z \). This is because when firm 1 spends less, its chance of winning the customer also decreases. As a result, firm 1 does not appropriate any surplus gain caused by the softened competition. When \( z \) is large, the increase in \( z \) intensifies the firm competition. Therefore, firm 1 does not benefit from the increase of \( z \) either.

In contrast, firm 2 can benefit from the increase of \( z \) when \( z \) is small. In this case, firm 1 competes less aggressively when it receives \( S = h \). This leads to a higher probability for firm 2 to win the customer. As a result, firm 2’s expected payoff when receiving \( \hat{S} = \tilde{h} \) increases due to the softened competition. Overall, firm 2 benefits from the increase of \( z \). Moreover, firm 2 actually appropriates all the surplus gain caused by the softened competition.

When \( z \) is large, firm 2 does not benefit from the increase of \( z \) either. In this case, the more similar information motivates firms to compete more aggressively by spending more. The more head-to-head competition hurts both
firms and as a result, firm 2’s expected payoff is also decreasing in \( z \).

We next consider firm 1’s incentive to share information with firm 2.

**Proposition 7.** (1) Firm 1 has no incentive to voluntarily share information with firm 2;

(2) When \( \Pr(h) \leq \frac{\sqrt{\gamma}}{2} \), firm 1 has no incentive to sell information to firm 2. When \( \Pr(h) > \frac{\sqrt{\gamma}}{2} \), firm 1 has the incentive to sell information to firm 2 (i.e., paid sharing) if \( z < z^* \), where \( z^* = \frac{1 - \sqrt{2(1 - \gamma)}}{2\gamma - 1} \) and \( \gamma = \Pr(h) \).

(3) In paid sharing, firm 1 increases \( z \) to \( z^* = \frac{1 - \sqrt{2(1 - \gamma)}}{2\gamma - 1} \) and firm 2 pays firm 1 a price of \( \pi_2(z^*) - \pi_2(z) \).

Proposition 7.1 indicates that firm 1 has no incentive to share information voluntarily (i.e., give away its information to firm 2 for free). The reason is that, as Proposition 6 shows, firm 1’s expected payoff is always decreasing when the two firms’ information become more similar. Although less information asymmetry may soften the firm competition under certain circumstances, firm 2 appropriates all the surplus gain and firm 1 does not benefit. Therefore, firm 1 has no incentive to give away its information to firm 2 for free.

Although firm 1 is not willing to give away its information for free, Proposition 7.2 indicates that firm 1 would like to sell its information to firm 2 under certain circumstances. This is because when \( \Pr(h) > \Pr(l) \) and \( z \) is small enough, allowing firms to have more similar information can increase the total surplus by softening the competition. Firm 1 has no incentive to voluntarily share information since it cannot appropriate the surplus gain in competition. If the surplus gain can be transferred from firm 2 to firm 1, firm 1 has the incentive to share information and improve the overall surplus. One way to transfer the surplus is to allow firm 1 charge a price for information sharing. For example, firm 1 can sell the dataset at a price. When firm 1 has the bargaining power, it can make a take-it-or-leave-it offer to firm 2. In this way, firm 1 can set the price in a way that all the surplus gain is transferred from firm 2 to itself. That is, the price that firm 2 pays to firm 1 is \( \pi_2(z^*) - \pi_2(z) \).

Another issue is the degree of information sharing. As Proposition 6 shows, when \( z \) is large, improving the relative precision \( z \) decreases both firms’ payoffs. In this regard, it is not optimal to completely equalize the firms’ signals (i.e., choosing \( z = 1 \)). Instead, firm 1 should control the degree of information sharing and choose an optimal level of \( z \). Proposition 7.2 presents the optimal \( z^* \) and illustrates that \( z^* \) is dependent (and only dependent) on \( \Pr(h) \). In other words, to what extent firm 1 would like to equalize the two firms’ information is dependent on the probability that firm 1 receives a high signal about the customer.

We can show that \( \frac{\partial z^*}{\partial \gamma} > 0 \), i.e., the optimal degree of information for firm 1 is increasing in \( \Pr(h) \) (note that \( \gamma = \Pr(h) \)). In other words, when it is more likely for firm 1 to receive a high signal about the customer, firm 1 is more willing to make the two firms’ information more similar. The rationale is that firm 1 can benefit from the paid information sharing only when it receives \( S = h \) (note that when firm 1 receives \( S = l \), it does not compete at all). Therefore, the more likely that firm 1 receives \( S = h \), the more willing that firm 1 is to soften the competition through information sharing.

The result of the optimal degree of information sharing also generates practical implications. Consider a numerical example. When \( \Pr(h) = \gamma = 0.75 \), the optimal relative precision \( z \) is \( z^* = \frac{1 - \sqrt{2(1 - \gamma)}}{2\gamma - 1} = 0.13 \). With this \( z^* \), we have \( \Pr(h | h) = \frac{z^*}{2} \approx 0.57 \) and \( \Pr(h) = \Pr(h | h)\Pr(h) + \Pr(h | l)\Pr(l) = 0.53 \). In other words, when firm 1 derives a high signal about the customer with a probability of 0.75, it should control the sharing of data and let firm 2 receives a high signal with a probability of 0.53. Similarly, if \( \Pr(h) = 0.9 \), we have \( z^* = 0.48 \) and \( \Pr(h) = 0.69 \). In other words, if firm 1 derives a high signal about the customer with a probability of 0.9, it should control the sharing of data and let firm 2 receives a high signal with a probability of 0.69.
Discussion and Conclusion

The main contribution of this paper is to examine the possibility of sharing individual-level customer information among competing firms which are horizontally undifferentiated. Using a common-value all-pay auction framework, this paper studies the competition between two firms in customer acquisition. These two firms only differ in their information about the value of each prospective customer their target. In contrast to the existing literature focusing on differentiated firms, we study the case where the customer has no brand preference. The study shows that even when firms compete head-to-head, information sharing can still soften the competition. The key reason is that when firms have asymmetric information, the less informed firm may bet on the chance that the better informed firm does not receive good signal about the customer, and thus the less informed firm competes aggressively. If the better informed firm reduces the information asymmetry by sharing customer data with the less informed firm, it mitigates the less informed firm’s opportunism and thus softens the firm competition. In this way, information sharing results in a win-win situation. We also find that the better informed firm is not willing to give away information for free. However, it has the incentive to sell the information at a price. The information price transfers the surplus gain (resulting from the softened competition) from the less informed firm to the better informed firm. The insights generated from this study help explain why information sharing may be desirable even between firms that compete head-to-head (without horizontal differentiation).

By identifying the conditions in which the better informed firms shares information, this study generates important managerial implications. The results suggest that the better informed firm’s incentive of information sharing is dependent on the probability that it detects the value signals (which indicate valuable customers) from the customer data. When the better informed firm feels that the data is less likely to generate value signals about customers, it never shares the data with its competitor. However, when the better informed firm feels that the data is very likely to generate value signals about customers, it may have the incentive to share the data with its competitor. An implication of these results is that good market conditions may encourage the practice of information sharing. In good markets with more valuable customers, the customer data is more likely to indicate valuable customers. Therefore, information sharing is more likely to arise. Another implication is that the information richness of customer data may also improve information sharing. When the customer data is rich in content so that the better informed firm is more likely to detect value signals about customers, the firm is also more likely to share its data with competitors. Therefore, managers of better informed firms can use the market conditions and the quality of customer data as guidance for their information sharing strategies.

This study considers the optimal degree of information sharing. In this case, the better informed firm can control to what extent it improves the less informed firm’s information. The results suggest that the degree of information sharing is also dependent on the probability that the better informed firm receives good signals about the customer. The more likely that the better informed firm receives good signals, the more information the better informed firm shares. The implication is that managers can also determine how much customer data to share with competitors based on the market conditions and the information richness of the customer data. When the market condition is good or the customer data is rich in content to suggest more valuable customers, the firm with the customer data can choose to share more to soften the competition.

The insights from this study, alongside that from the existing literature (e.g., Chen et al. 2001), generate more implications for inter-firm sharing of customer data. When firms distinguish loyal customers from shoppers, they can adopt different sharing strategies for different customer data. Firms can maximize the sharing of their loyal customers data. By disclosing loyal customers to the largest extent, firms can minimize the competitors’ poaching activities. For the data on shoppers, firms can choose to share it partially. The different sharing strategies for different customer data allow firms to mitigate competition and improve their profitability on different customer segments. In this regard, our model can be extended to the case where firms sell to partially overlapped customer bases and they share with each other the data on different groups of customers.

Another interesting finding of this study is that considering all contingencies of signals, the better informed firm and the less informed firm spend similarly in customer acquisition on average. In other words, information does not influence firms’ general competitive aggressiveness. However, information does influence the effectiveness of firms’ customer acquisition spending. For the better informed firm, it can focus more of its spending on the more promising customers. Therefore, the better informed firm’s expected payoff is always higher than that of the less informed firm.
The study also provides many opportunities for future research. First, the information sharing between competing firms is often facilitated by other organizations such as the customer data intermediaries who provide data service to competing firms (e.g., Pancras and Sudhir 2007). Also, competing firms in the same industries may join trade associations which enable the information sharing (e.g., Vives 1990). The role of these third-party organizations in sharing customer information between undifferentiated firms, is worth studying. Second, many key results of this study suggest that the information richness of the customer data influences the information sharing practices. Future research may consider more strategic actions of firms or customer data intermediaries in improving the information richness of shared customer data. This may generate more interesting insights on the information sharing between competing firms. Finally, our study suggests that the difference in the firms’ customer information does not lead to the difference in the firms’ general competitive aggressiveness in customer acquisition. Future study may further examine the welfare implications of sharing customer information by considering different ways of firm competition.

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