Chapter II

Information Transparency Hypothesis: Economic Implications of Information Transparency in Electronic Markets

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Abstract

This chapter explores the private and social desirability of information transparency of a business-to-business (B2B) electronic market that provides an online platform for information transmission. The abundance of transaction data available on the Internet tends to make information more transparent in B2B electronic markets. In such a transparent environment, it becomes easier for firms to obtain information that may allow them to infer their rivals’ costs than in a traditional, opaque market. How then does this benefit firms participating in the B2B exchanges? To what extent does information transparency affect consumers and the social welfare in a broader sense? Focusing on the informational effects,
this study explores firms’ incentives to join a B2B exchange by developing a game-theoretic model under asymmetric information. We then examine its effect on expected profits, consumer surplus, and social welfare. Our results challenge the “information transparency hypothesis” (that is, open sharing of information in electronic markets is beneficial to all participating firms). In contrast to the popular belief, we show that information transparency could be a double-edged sword. Although its overall effect on social welfare is positive, its private desirability is deeply divided between producers and consumers, and even among producers themselves.

Motivation

Despite the controversies surrounding B2B online exchanges, the Internet-based electronic marketplaces are considered to have the potential to reduce transaction costs, add product and pricing transparency, generate market liquidity, and facilitate bidding by a broad spectrum of potential suppliers in a standardized platform (Mullaney, 2003). Here we define a B2B marketplace as an online platform that creates a trading community linked by the Internet and provides the mechanism for B2B interactions using industry-wide data standard and computer systems. Online B2B exchanges allegedly streamline information flow in supply chains (Lee & Whang, 2000) and make the information more widely available (Agrawal & Pak, 2002). The re-balance of information asymmetry is an important motivation for establishing B2B exchanges (Hoffman, Keedy & Roberts, 2002). Yet, given these multiple benefits, why is it that B2B exchanges have not been widely adopted? Why are suppliers still reluctant to join a high-profile exchange such as Covisint (Koch, 2002)? B2B exchanges indeed seem to improve information transparency, but is information transparency a benefit or a threat? It has been a popular belief that open sharing of information in electronic markets is beneficial to all participating firms, which we term as the “information transparency hypothesis.” One of the objectives of our chapter is to scrutinize these kinds of claims by economic analysis.

Information technology (IT) has in general improved the flow of information (Zhu, 1999). B2B electronic exchanges in particular provide an online platform through which information is gathered, compiled, displayed, and transmitted...
among participating companies (Zhu, 2002). In this sense, online B2B exchanges play a role of transmitting or aggregating information within a particular industry (Hansen, Mathews, Mosconi & Sankaran, 2001). Examples include Covisint in the automobile industry, and Exostar in the aerospace industry.¹

The proliferation of these Internet-based marketplaces creates a vast sea of information about products, prices, transactions, and costs. Today a significant flow of information is being exchanged between buyers and sellers, between suppliers and manufacturers, and among competitors. This makes information more transparent in electronic markets than in traditional physical markets. Information transparency is defined as the degree of visibility and accessibility of information. The subject of information in the context of electronic markets has gained the interest of both academics and practitioners. Bakos (1998) describes the three main functions of markets: matching buyers and sellers, facilitating the exchange of information, and providing an institutional infrastructure. In this chapter we focus on the second role, as the digitization of information combined with high-speed networks has heightened the role of information in electronic markets. Data are real time, more transparent, and more synchronized; information flows more instantaneously in electronic markets (Grover, Ramanlal & Segars, 1999). In this regard, information transparency becomes one of the key features that distinguish digital exchanges from traditional markets (Zhu, 2002).

The Internet increases information transparency in several ways. The Internet in general not only contains abundant information but also reduces the search cost for that information (Bakos, 1997). More specifically, using reverse-auction bidding, XML mapping, data mining, and intelligent agent technologies, online exchanges allow participants to obtain information that might be useful to infer rivals’ costs more easily than they can with traditional markets in which inferring costs has been cumbersome (Sinha, 2000). It is often the case that data regarding prices, quantities, and bidding specifications are recorded in a database and made available to participants of the exchanges. For instance, on Covisint, suppliers can see who is selling brakes and clutches, at what prices, and in what quantities. As posted on its Web site (www.covisint.com), “Covisint allows you to quickly share critical information . . . and to browse, as well as receive and transmit electronic information.” There are many such real-world examples illustrating that cost information is more transparent on electronic exchanges than in traditional markets.²

In this chapter we leave out the details of the process of price discovery and information transmission. Instead we focus on the equilibrium effects of such
information transmission. Transparent information is typically regarded as a good thing due to possible efficiencies arising from more widespread dissemination of accurate information. Yet, “to have a full collaborative environment is a hard sell for me … what I am going to lose in terms of visibility and exposing my information to potential competitors is greater than what I would gain on the collaboration side” (Meehan, 2001). Indeed, are B2B exchanges likely to promote efficiency and yield social welfare benefits, or are they more likely to be used to squeeze margins and impose price pressure on small suppliers? This possibility is evidenced by the concern being expressed by suppliers over the power that carmakers may wield through the Covisint exchange (FTC, 2000). That there are risks, as well as potential gains, associated with possible cost information exchange via online marketplaces is reflected in the investigations conducted by regulation authorities on several B2B exchanges (CRN Business Weekly, 2000; Disabatino, 2002; FTC, 2000).

These issues give rise to a set of critical research questions regarding the informational role of online B2B marketplaces. We are concerned with the private incentives and social welfare of information exchange. Research questions of particular interest include:

- What incentives will firms have to join the B2B exchange?
- Will the introduction of the B2B exchange benefit the industry?
- How does information transparency benefit (or hurt) consumers and society in a broader sense?

Intuitively, information aggregation tends to have two types of effects: the direct effect on the firm and the cross effect on its rivals (Zhu, 2004). First, receiving more accurate information permits the firms to choose the strategies that are more finely tuned to the actual state of the market and hence improve the profits, so the increased transparency of information for a firm has a positive effect. On the other hand, transparent information may affect the degree of correlation among the strategies of all other firms. The increased strategy correlation and the increased precision of the rivals have a rather subtle, complicated effect on the behavior of the firms. The equilibrium behavior is not clear without a rigorous model.

Seeking to better understand these issues, we built a simple game-theoretic model, with some abstractions and assumptions, so that we can begin to study the informational effects of B2B marketplaces. We utilized the concept of
fulfilled rational expectations equilibrium with incomplete information. One implication of this equilibrium concept is that the market participants incorporate the information that is contained in the equilibrium strategies in their decision-making process. This reflects the aggregation and transparency of information in a market mechanism with very little friction, such as an Internet-based B2B exchange (Zhu, 2004).

Our model shows that firms’ incentives to join a B2B exchange are sensitive to their relative cost positions. Firms with heterogeneous costs have different incentives for information exchange. We also find that information transparency benefits some firms but hurts others. For substitute products, profits and market share will be redistributed from high-cost firms to low-cost firms. Under the assumptions of our model, producer surplus will rise due to more efficient allocation of production quantities, yet consumer surplus can be higher or lower.

**Relationship to Other Studies**

Due to the recent emergence of B2B exchange as a recognizable economic phenomenon, prior research aimed directly at the questions posed here has been limited (Kauffman & Walden, 2001). Some more general theory, however, has been developed in the literature of industrial organization and information economics. The literature has shown steady interest in the issue of information sharing among oligopolists, which had an early start with Novshek and Sonnenschein (1982) and Clarke (1983) and was continued by Vives (1984), Gal-Or (1986), Vives (1990), and Malueg and Tsutsui (1998), among others. All of these papers considered information sharing about market demand in a duopoly context. In those typical models with demand uncertainty, firms are uncertain about the intercept of a linear demand curve (where all firms face the same common disturbance in their demand functions). Papers about cost uncertainty are relatively rare. Shapiro (1986) and Li (1985) considered information sharing about costs among Cournot oligopolists, both motivated by an antitrust perspective and focused on whether information sharing would make the market more or less competitive. In contrast our perspective is about the incentive and welfare implications of information transparency on B2B exchanges. Their models assumed homogeneous products, linear demand, and constant marginal cost. They studied two extreme information-sharing scenarios: either industry-wide complete information pooling or no information
sharing at all. We build on these studies, particularly the game-theoretic modeling of information sharing among oligopolists, and address additional concerns arising in the B2B exchange context. After we present our model, we will re-visit this issue and compare our results with the literature.

The remainder of the chapter proceeds as follows. The next section presents the basic setup of the model. The incentives section analyzes firms’ incentives to join a B2B exchange. The welfare implications section extends the model to analyze the broader welfare effects on the industry, the consumers, and the society. Implications are discussed in the final section. To stay within the page limit, we emphasize the economic rationale rather than mathematical derivations.5

**Model**

We consider a market in which there are a finite number of \( n \) suppliers \((n \geq 2)\), and each firm’s technology is subject to uncertainty. They can trade through either traditional bilateral contracting or a neutral B2B online exchange. The B2B exchange makes certain transaction data visible on its Web site. The sequence of events occurs as follows: (1) each firm decides whether or not to join the B2B exchange with an understanding that the B2B exchange will make signals regarding its cost data visible to other exchange members; (2) with its own cost data endowed initially, each firm may access additional information about other firms’ costs on the B2B exchange, depending on its decision from stage (1); and (3) each firm chooses its output level, conditional on its information set from stage (2). This three-stage timing structure is illustrated in Figure 1. Notice that firms make decisions simultaneously, and they do not announce their participation decisions until the game is over.

We use a simple linear demand function to represent the buying side:

\[
p_i = d - q_i - \theta \cdot \sum_{j \neq i} q_j, \quad i = 1, 2, ..., n
\]

Here \( p_i \) is the price, \( q_i \) is the quantity, \( d \) is the demand intercept, and \( \theta \) denotes the degree of product differentiation where products are substitutes, comple-

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5 Note that the reference to the page limit is not necessary in the text. It is added here for context.
ments, or independent, depending on whether \( \theta > 0, \theta < 0, \) or \( \theta = 0 \). We assume there is a continuum of buyers in the market so that their individual decisions do not influence the market outcome. This allows us to focus on the strategic interactions of the suppliers.

The technology is stochastic and exhibits constant returns to scale. In other words, each firm employs a technology with a marginal cost, denoted by \( c_i \) for firm \( i \):

\[
C_i(q_i) = c_i q_i + F, \quad i = 1, 2, \ldots, n.
\]  \hspace{1cm} (2)

That is, each firm’s marginal cost \( c_i \) is a random variable. \( F \) is the constant fixed cost. The cost vector \( c = (c_1, c_2, \ldots, c_n)' \) follows an \( n \)-dimensional multivariate normal distribution. Its joint distribution is defined by \( c \sim N(\mu, \Sigma) \) with mean \( \mu \in \mathbb{R}^n \) and covariance matrix \( \Sigma \in \mathbb{R}^{n \times n} \), where \( \mu_1 = \ldots = \mu_n = \mu > 0 \) and

\[
\Sigma = \begin{pmatrix}
\sigma^2 & \rho \sigma^2 & \ldots & \rho \sigma^2 \\
\rho \sigma^2 & \sigma^2 & \ldots & \rho \sigma^2 \\
\vdots & \vdots & \ddots & \vdots \\
\rho \sigma^2 & \rho \sigma^2 & \ldots & \sigma^2
\end{pmatrix}_{n \times n}
\]  \hspace{1cm} (2')

where \( \rho \) is the correlation coefficient between any pair \( (c_i, c_j) \) \( j \neq i \) with \( \rho \in (0,1) \).

Figure 1. Sequence of events
While the joint normal distribution $N(\mu, \Sigma)$ is common knowledge, an individual firm’s cost is private information. Without the B2B exchange, firm $j$ observes only its own cost, $c_j$, but not those of the other firms. In contrast, member firms in the B2B exchange may have access to additional information — they observe signals that are correlated to the costs of the firms trading on the B2B exchange, $(c_1, \ldots, c_n)$, where $0 < k \leq n$.

We restrict our attention to a class of distributions such that the conditional expectations obey a linear property, namely, Linear Conditional Expectation (LCE) property (Zhu, 2004):

$$E[c_j | c_i] = \mu + \rho (c_i - \mu), \quad i, j = 1, \ldots, n; \ i \neq j. \quad (3)$$

Further, given the cost information of any subset $K \subseteq N$, one can form the conditional expectations for $c_j, j \in N \setminus K$, as:

$$E[c_j | c_1, \ldots, c_k] = \mu + \frac{\rho}{1 + \rho (k - 1)} \sum_{i \in K} (c_i - \mu), \quad \text{for } j \in N \setminus K. \quad (4)$$

Notice that for $k = 1$, conditional expectation (4) reduces to (3). It has been shown that the LCE property in (3) and (4) is valid for multivariate normal distribution (Basar & Ho, 1974; Shapiro, 1986). The LCE property means that, for a multivariate normal distribution, its regression equations (conditional means) are linear functions of the conditioning variables. The parameters of the regression functions are determined by the covariance structure (that is, $\rho$). Given their information sets upon joining the B2B exchange, firms will update their conditional belief about other firms’ cost, and the conditional expectations obey a linear function. That is, $c_j (i \in K)$ can be used to update posterior expectations on $c_j$ via the mechanism specified by (3) and (4).

The notion of fulfilled expectations equilibrium requires not only that firms maximize expected profit given their information set, but also that their strategies not be controverted. This means that, when each firm uses its conditional distribution in (4) and maximizes expected profit as a Bayesian-Nash equilibrium, the realized distribution is precisely the one given by the conditional belief that is held by the firm (Zhu & Weyant, 2003).
We focus on the informational consequences of joining the B2B exchange. After firm $i$ joins the exchange, its trading activities will be recorded in the exchange database, which may reveal its cost, $c_i$, to other member firms belonging to the exchange. In return it can observe the costs of other firms that are also trading on the exchange. The set $N = (1, 2, \ldots, n)$ of all $n$ firms is partitioned into two subsets, the set $K$ of $k = |K|$ firms that join the B2B exchange and its complement set $N \setminus K$ of $(n-k)$ firms that trade outside of the B2B exchange (e.g., through traditional bilateral negotiation and contracting). This is shown in Figure 2. Hence, the essential difference between the two sets of firms is their distinct information structures.

By this construction, the set of firms in $K$ obtains information from their participation in the B2B exchange to which no firm in $N \setminus K$ belongs. Their information set is:

\[ I_i = \{c_1, \ldots, c_i, \ldots, c_k\} \quad \text{for} \quad i \in K, \quad (5) \]

where $I_i$ denotes the information set available to firm $i$. Joining the B2B exchange revises firm $i$’s information set from $\{c_i\}$ to $\{c_1, \ldots, c_i, \ldots, c_k\}$. For the $(n-k)$ firms in the set $N \setminus K$ that trade outside of the B2B exchange, each firm’s information set is confined to its own cost. That is:

\[ I_j = \{c_j\} \quad \text{for} \quad j \in N \setminus K. \quad (6) \]

Figure 2. B2B exchange members and non-members as two subsets
To sum up this section, we have made the following assumptions:

**A1:** Demand and cost functions are represented by (1) and (2);

**A2:** Firms use (3) and (4) to update their conditional belief about rivals’ costs;

**A3:** The B2B exchange facilitates information transparency in the sense that observed transaction data are perfectly correlated with costs (i.e., no noise in the signals).

**A4:** The transmission of information can only be done through the B2B exchange.6

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**Incentives to Join the B2B Exchange**

Given the above assumptions and the model setup, we proceed to derive the equilibrium quantities and profits under two information structures. Firms maximize their expected profits by choosing output levels non-cooperatively for the given information structure, assuming that all other firms behave the same; namely, they play a Cournot game. Following the standard game-theoretic approach (Fudenberg & Tirole, 1991), the equilibrium notion we use is that of a Bayesian-Nash equilibrium, which requires that each firm’s strategy be a best response to its conjectures about the behavior of the rivals, consistent with their beliefs about other firms’ costs (Tirole, 1988). By backward induction, we first examine the last stage (optimal quantities) and then work backward to analyze the first stage (whether to join the B2B exchange).

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**Optimal Quantities**

We derive the optimal strategies corresponding to two different information sets in (5) and (6) associated with B2B exchange members and non-members, respectively. Given the demand function in (1) and cost function in (2), profit can be computed as:

\[ \pi_i = (p_i - c_i)q_i = \{d - q_i - \theta \sum q_j - c_i\} q_i. \]
Taking expectations, conditional on its information set $I_i = \{c_1, \ldots, c_k\}$, a member firm $i$ maximizes its expected profit:

$$\max_{q_i} E[\pi_i | I_i] = \{d - q_i - \theta \sum_{m=1}^{k} E[q_m | I_i] - \theta \sum_{j=k+1}^{m} E[q_j(c_j) | I_i] - c_i\} q_i,$$

$$i \in K$$  \hspace{1cm} (7)

Solving the first order conditions jointly yields the following optimal quantity (Zhu, 2004):

$$q_i^* = \bar{q} + \psi \sum_{m=1}^{k} (c_m - \mu) - \phi (c_i - \mu), \quad i \in K,$$

\hspace{1cm} (8)

where

$$\bar{q} = \frac{d - \mu}{2 + (n - 1)\theta}$$

$$\psi = \frac{1}{k\theta + 2 - \theta} \left[ \frac{\theta}{2 - \theta} + \frac{\beta \rho \theta (n - k)}{1 + \rho (k - 1)} \right]$$

$$\phi = \frac{1}{2 - \theta}, \quad (\theta \neq 2)$$  \hspace{1cm} (9)

where $\bar{q}$ is the equilibrium quantity in the absence of cost uncertainty (that is, if output were all produced at a constant cost, $\mu$). Sensitivity coefficient $\phi$ represents a “direct” adjustment to the firm’s own cost, and $\psi$ represents a “counter” adjustment to rivals’ costs. Sensitivity $\psi$ also depends on non-members’ behavior, $\beta$, which will be determined soon. This means that the “direct” and “counter” adjustments by the member firms involve the behavior of the non-members. Examining the equilibrium quantities in (8) leads to the following observation:
Lemma: The equilibrium strategy for each firm in the B2B exchange is affine in its private cost, $c_j$, as well as in the revealed cost data from the exchange, $(c_1, \ldots, c_k)$, with direct adjustment $\phi$ and counter adjustment $\psi$ to the cost information.

Now consider the profit-optimization problem of a non-member firm, $j \in N \setminus K$. Not having access to the information aggregated on the B2B exchange, each firm’s information set is confined to its own private cost data, $c_j$, at the time when it makes its output decisions. Firm $j$ maximizes its expected profit, conditional on its information set, $I_j = \{ c_j \}$:

$$
\max_{q_j} E[\pi_j | I_j] = \{ d - q_j - \theta \sum_{i=1}^{k} E[q_i | c_j] - \theta \sum_{m=k+1}^{n} E[q_m | c_j] - c_j \} q_j,
$$

$$
\text{subject to}\; j \in N \setminus K
$$

Solving the first order conditions yields (Zhu 2004):

$$
q_j^* = \overline{q} - \beta (c_j - \mu),
$$

where

$$
\beta = \frac{[1 + \rho(k-1)][2 + (k-1-\rho k)\theta]}{[2 + \theta \rho (n-k-1)][2 + (k-1)\theta][1 + \rho (k-1)] - k^2 \theta^2 \rho^2 (n-k)}
$$

The equilibrium strategy for a non-member firm is a linear function of the base quantity, $\overline{q}$, and its private cost, $c_j$, adjusted by sensitivity coefficient $\beta$. The coefficients $\phi$, $\psi$, and $\beta$ represent the behavior of the member and non-member firms.
Equilibrium Profits

In order to analyze the formation of the B2B exchange, it is necessary to derive and compare the equilibrium profits for members $E[\pi_i^*]$ and non-members $E[\pi_j^*]$, respectively, for any given exchange membership size, $k$, where $k = |K|$, $K \subseteq N$. Substituting the optimal strategies, $q_i^*$ in (8) and $q_j^*$ in (12), into the profit functions in (7) and (11), and using the conditional expectations (3) and (4), we derive the following result:

**Proposition 1 (equilibrium profits):**

In equilibrium, a member can expect to make a profit as:

$$
E(\pi_i^*) = [E(q_i^*)]^2 + \psi^2 (k-1)[1+(k-2)\rho] \sigma^2, \quad i \in K. \quad (14)
$$

A non-member can expect to make a profit as:

$$
E(\pi_j^*) = [E(q_j^*)]^2, \quad j \in N \setminus K. \quad (15)
$$

Here, $\psi^2 (k-1)[1+(k-2)\rho] \sigma^2 > 0$, the expected profits of the exchange members increase in the variance of the cost, $\sigma^2$. This reflects the convexity of profits as a function of costs. It can be shown $\partial \Delta \pi / \partial \sigma^2 = \psi^2 (k-1)[1+(k-2)\rho] > 0$, then:

**Corollary 1 (property of convexity):** Firms would have stronger incentives to join the B2B exchange when they face higher uncertainty, that is, $\partial \Delta \pi / \partial \sigma^2 > 0$.

Term $\psi^2 (k-1)[1+(k-2)\rho] \sigma^2$ represents the benefits of information aggregation on the B2B exchange. It would be more valuable when the uncertainty, $\sigma^2$, is higher. This result is consistent with our positioning conceptualized earlier that B2B exchange serves as an information-transmission platform.
Who Will Join the B2B Exchange?

Having derived the optimal outputs and equilibrium profits, we are now prepared to determine whether the firms in the exchange can expect to make higher profits than the non-members. Each firm considers information exchange beneficial in the classical Pareto-dominance sense when \( E[\pi_i^*] > E[\pi_j^*] \), for any given exchange size, \( k, i \in K \) and \( j \in N \setminus K \).

To compare the expected profit of joining the exchange versus staying offline, we need to quantify the expected profit difference, \( \Delta \pi = E[\pi_i^*] - E[\pi_j^*] \), from (14) and (15), as:

\[
\Delta \pi = [E(q_i^*)]^2 - [E(q_j^*)]^2 + \psi^2 (k - 1)[1 + (k - 2)\rho] \sigma^2.
\]

Defining \( \Delta c \equiv c_i - \mu \), and plugging the expectations of (8) and (12), \( \Delta \pi \) can be written as a quadratic function of \( \Delta c \):

\[
\Delta \pi = (\psi - \phi + \beta)(\psi - \phi - \beta) (\Delta c)^2 + 2(\psi - \phi + \beta) \bar{q} \Delta c + \psi^2 (k - 1)[1 + (k - 2)\rho] \sigma^2.
\]

By examining its first and second derivatives, we found that \( \Delta \pi \) is a convex, U-shaped curve. Solving the equation \( \Delta \pi = 0 \) yields:

\[
\hat{c} = \mu + \frac{\bar{q} - \sqrt{\bar{q}^2 - \frac{\psi - \phi - \beta}{\psi - \phi + \beta} \psi^2 (k - 1)[1 + (k - 2)\rho] \sigma^2}}{\phi + \beta - \psi}, \tag{16}
\]

where \( \hat{c} \) represents the threshold cost below which \( \Delta \pi \geq 0 \). That is, when \( c_i \leq \hat{c} \), \( E[\pi_i^*] \geq E[\pi_j^*] \). This implies that firms with low cost, \( c_i \leq \hat{c} \), will have an incentive to join the B2B exchange, as they will derive higher profits than if they stay offline. In contrast, firms with high cost, \( c_i > \hat{c} \), will lack the incentive to join the B2B exchange. This is summarized next.
Proposition 2 (equilibrium solution – who will join the B2B exchange):
Cost heterogeneity induces different incentives to join the B2B exchange. In equilibrium, low-cost firms will find it optimal to join the online exchange while high-cost firms will not. That is:

\[
\Delta \pi = \begin{cases} 
\geq 0, & \text{if } c \leq \hat{c} \\
< 0, & \text{if } c > \hat{c}
\end{cases}
\]

where threshold cost \( \hat{c} \) is defined in (16).

The basic tradeoff that drives the incentives for a firm to trade on the B2B exchange is the increased precision of information, decomposed in the effect on the firm itself and on its rivals, and the correlation induced in the strategies of the firms. By making cost data more transparent and by “advertising” their relatively aggressive reaction curves, the low-cost firms induce the rivals to shrink their outputs. This leads to a more efficient allocation of output (and market share) than what would arise in the absence of information transparency. Without the transparent information facilitated by the B2B exchange, all firms would estimate their rivals’ costs based on their limited private information, which tends to make their estimates around the mean of the cost, \( \mu \). With the B2B exchange, the fog clears out and the firms can see through each other’s costs better than before. In the new information-transparent equilibrium, more efficient firms produce more. Hence the mix of output (and market share) is shifted from high-cost firms to low-cost firms. This would result in very different incentives toward information transparency on the B2B exchange: in equilibrium we will find that low-cost firms will prefer to trade on the transparent online exchange, while high-cost firms will have incentives to trade in an opaque environment where they can hide their “uncompetitive” costs.

With the result in Proposition 2, we can now make the notion of “low-cost” and “high-cost” more precise. Low-cost firms are those firms whose costs are below the critical level, that is, \( c_i < \hat{c} \). High-cost firms are those whose costs are above the critical level, that is, \( c_i > \hat{c} \). That is, \( c_H = \{ c_i, \forall c_i > \hat{c} \} \) and \( c_L = \{ c_i, \forall c_i \leq \hat{c} \} \). This cost heterogeneity permits the possibility of a separating equilibrium as follows.
Corollary 2 (separating equilibrium): In equilibrium, those firms trading through the B2B exchange are expected to be the more efficient (with lower costs or better technology) firms, while those less efficient (higher-cost) firms continue to trade through the traditional markets such as bilateral contracts or negotiation.

Given the separating-equilibrium nature induced by information transparency, the mere existence of the online exchange makes it more difficult for high-cost firms to hide their cost data. The B2B exchange as a new technology helps the market to sort out efficient firms from inefficient ones. Besides information revealed from online transactions data, the action to join or not to join the B2B exchange itself may single out the high-cost firms. For example, if firm $j$ chooses to stay away from the B2B exchange, then other firms could infer that firm $j$ is likely to be a high-cost firm (although they still do not know firm $j$’s exact cost). Therefore, even though they choose not to participate in the online marketplace, high-cost firms are made worse off by the mere existence of the B2B exchange in the industry.

Finally, it can be shown that:

$$\frac{\partial \hat{c}}{\partial \sigma^2} > 0,$$

meaning if $\sigma^2 \uparrow$, then $\hat{c} \uparrow$, so more firms will find it profitable to join the exchange. Consequently, when uncertainty of information rises, firms would have stronger incentives to participate in the B2B exchange, and the exchange’s membership size and critical mass will increase. Hence uncertainty works to the advantage of the B2B exchange and its members.

Welfare Implications:  
Private and Social Desirability of Information Transparency

We have explored the incentives for individual firms to join a B2B exchange that serves as an information exchange mechanism. Yet to what extent does greater
information transparency affect the welfare of producers, consumers, and the society in a broader sense? Especially, how does B2B exchange benefit (or hurt) consumers? To answer these questions, we now proceed from private incentives to social consequences of B2B information exchange and examine the welfare implications for the industry, consumers, and society.

We do so by comparing the opaque and transparent information equilibria on an \textit{ex ante} basis. Specifically, based on firm’s equilibrium quantities and expected profits shown in the previous section, we first derive the expressions of producer surplus ($PS$), consumer surplus ($CS$), and social welfare ($SW$). Then we examine whether information transparency is socially beneficial by comparing these welfare terms under two information structures, corresponding to the two scenarios with and without the B2B exchange.

The welfare measures can be expressed in terms of variance and covariance of output quantities and costs. Starting from expected profit, we have:

\[
E[\pi_i] = E(p_i q_i) - E(c_i q_i) = Cov(p_i q_i) + E(p_i) E(q_i) - Cov(c_i q_i) - E(c_i) E(q_i)
\]

\[
= \pi_i + Cov(p_i q_i) - Cov(c_i q_i)
\]

(17)

where $\pi_i = (E(p_i) - \mu) E(q_i)$ represents the baseline profit without cost uncertainty. Using (1), it is straightforward to show:

\[
Cov(p_i q_i) = -Var(q_i) - \theta \sum_{j \neq i} Cov(q_i q_j).
\]

Inserting it into (17) yields:

\[
E[\pi_i] = \pi_i - \left[ Var(q_i) + Cov(c_i q_i) \right] - \theta \sum_{j \neq i} Cov(q_i q_j),
\]

(18)

where the first term represents single-firm \textit{own effect} and the second represents multi-firm \textit{interaction effect}. The own effect means the effect on the firm itself, while the interaction effect means the cross effect that involves other firms.
Let $E[PS]$ denote the expected producer surplus. Then from (18), we have:

$$E[PS] = \sum_i E[\pi_i] = \overline{PS} - \sum_i \left[ \text{Var}(q_i) + \text{Cov}(c_i, q_i) \right] - \theta \sum_i \sum_{j \neq i} \text{Cov}(q_i, q_j),$$

where $\overline{PS} = \sum_i \overline{\pi_i}$. Similarly, expected consumer surplus, $E[CS]$, can be obtained as:

$$E[CS] = \overline{CS} + \frac{1}{2} \sum_i \left[ \text{Var}(q_i) \right] + \frac{1}{2} \theta \sum_i \sum_{j \neq i} \text{Cov}(q_i, q_j).$$

If we sum the expected producer and consumer surpluses, we get the expected social welfare as follows:

$$E[W] = E[PS] + E[CS] = \overline{W} - \sum_i \left[ \frac{1}{2} \text{Var}(q_i) + \text{Cov}(c_i, q_i) \right] - \frac{1}{2} \theta \sum_i \sum_{j \neq i} \text{Cov}(q_i, q_j),$$

where $\overline{W} = \overline{PS} + \overline{CS}$, in which $\overline{CS}$, $\overline{PS}$, and $\overline{W}$ show the baseline welfare terms without cost uncertainty.

Since the signs of $\theta$ and $\text{Cov}(q_i, q_j)$ always go opposite, we introduce an interaction measure to integrate these two cross-effect parameters as follows:

$$\text{Int}(q_i, q_j) = -\theta \text{Cov}(q_i, q_j), \quad i \neq j.$$

This interaction measure represents the degree of interaction between any pair of firms $(i, j)$, $i \neq j$. Equations (19) ~ (21) can be rewritten in terms of $\text{Int}(q_i, q_j)$ as follows:
where the own effect is further decomposed into variation effect (on the revenue side) and allocation effect (on the cost side).

Next we compare these terms under two information structures — shared information and private information — corresponding to the two scenarios with and without the B2B exchange. The difference of $PS$, $CS$, and $SW$ are respectively:

$$\Delta E[PS] = -\sum_i [\Delta Var(q_i)] + \sum_i \Delta Cov(-c_i, q_i) + \sum_{j \neq i} \Delta Int(q_i, q_j),$$

$$\Delta E[CS] = \frac{1}{2} \sum_i [\Delta Var(q_i)] - \frac{1}{2} \sum_{j \neq i} \Delta Int(q_i, q_j),$$

$$\Delta E[SW] = -\frac{1}{2} \sum_i [\Delta Var(q_i)] + \sum_i \Delta Cov(-c_i, q_i) + \frac{1}{2} \sum_{j \neq i} \Delta Int(q_i, q_j).$$

It becomes clear from equations (26) ~ (28) and (22) that the relative strength of the following four components plays a key role in measuring the welfare of producers, consumers, and the society: (i) $Var(q_i)$, (ii) $Cov(c_i, q_i)$, (iii) $Cov(q_i, q_j)$, and (iv) $\theta$. The first two terms constitute the own effect, and the last two constitute the interaction effect. By combining these factors, we may have a very useful way of tracing out the welfare effect of information transparency. First, information aggregation tends to increase the variance of individual output, that is, $\Delta Var(q_i) \geq 0$. In other words, information exchange among
producers tends to increase the variance of each firm’s output, as a more flexible adjustment of each firm’s production activity is facilitated. From equations (26) ~ (28), increases in variance, $\text{Var}(q)$, will raise consumer surplus but lower producer surplus and social welfare. This is consistent with a well-known theme in the economics literature: in markets with uncertainty, increases in variance raise expected consumer surplus as consumer surplus is a convex function of output (Gal-Or, 1986; Vives, 1984).

Second, information transparency among producers tends to contribute to the efficient allocation of resources across firms in the following sense: the lower-(higher-) cost firms are likely to increase (decrease) their outputs in response to more accurate information about the cost vector, as shown in (8) and (12). That is, information transparency will increase the covariance between $(-c, q)$ and $q$, or $\Delta \text{Cov}(-c, q) > 0$. Therefore, the mixture of outputs (and market share) is shifted toward more efficient firms in the presence of greater information transparency. This allocation effect is shown to be beneficial to the industry and the society as in (26) and (28), where the benefit arises from a better correspondence between costs and outputs.

Third, comparing these terms inside and outside the B2B exchange, it can be shown that:

$$\Delta \text{Int}(q, q) = -\theta \Delta \text{Cov}(q, q) > 0, \quad i \neq j. \quad (29)$$

This means that information transparency tends to reinforce the degree of interaction between the output strategies of the firms. Information transparency tends to make the market more “uniform” (increasing the correlation of the firms’ strategies). It is clear from equations (26) ~ (28) that higher degree of interaction will benefit producers, but it will make consumers worse off. Intuitively speaking, the interaction among member firms tends to strengthen their cooperation, which helps member firms to form an implicit coalition. The welfare position of consumers as outsiders is weakened. The overall effect on social welfare is still positive, though.

By putting these three effects together and based on (26) ~ (28), albeit a tedious process, we can show the following result:

**Proposition 3 (Welfare effects on producers, consumers, and society):**

Producer surplus will rise due to more efficient allocation of production...
quantities. Yet consumer surplus can be higher or lower, depending on the relative strength of the variation effect and the allocation effect. The overall effect on social welfare will be positive.

Proposition 3 suggests that information transparency facilitated by the B2B exchange affect producers and consumers differently. The industry as a whole is better off because the interaction effect and allocation effect together tend to dominate the variation effect. But this benefit is not uniform among individual producers. The high-cost firms will be worse off, because profits will be redistributed from high-cost firms to low-cost firms.

Information exchange among producers may have a rather complicated effect on consumers. It may hurt consumers in some situations, but may benefit them in other situations. $\Delta E[CS]$ may move in either direction, depending on the relative strength of the variation effect and the interaction effect. When goods are moderately substitutable and costs are reasonably correlated (i.e., $\theta > 0$ and $\rho < 1$), information sharing benefits consumers. Otherwise, it is harmful for consumers.

Looking from another angle, the combined forces of such technological and stochastic interactions measure the degree of intermixture of competition and cooperation among firms. Our model shows that in the Cournot world under cost uncertainty, if the combined interaction is positive and strong (for example, when products are complements) then firms become mutually complementary rather than competitive, as there appears to be much room for cooperation among producers. The result is that cooperation through information aggregation will benefit participating firms, but it may hurt consumers. In this case, the firms’ incentives to form the B2B exchange may be socially excessive, and anti-competitive concerns may become legitimate as producers’ and consumers’ interests collide regarding information transparency of the B2B exchange. Then the FTC’s concern might be justified in such a situation (CRN Business Weekly, 2000; Disabatino, 2002).

**Comparison with the Literature**

To close this section, it is worth noting the differences between our results and the literature. As mentioned earlier, the closest studies to our model might be Shapiro (1986) and Li (1985). Several differences exist between our chapter
and theirs. The differences lay primarily in the information structure, in terms of both the type of information and the mechanism that the information is being transmitted. For example, those papers examined a situation where all firms received the resulting aggregate information. Only anonymous, aggregate statistics of firms’ cost data was disclosed. This feature is more representative of a public agency (for example, a census bureau or trade association) than a B2B exchange. By contrast, in our model, cost data at the individual firm level can be inferred from the B2B exchange. It can transmit much deeper firm-specific data about costs than other mechanisms previously available. The different assumptions about the role of the underlying technologies entail different setup of the model, and we show that these different models lead to very different equilibrium outcomes.

As a consequence of this setup, the result was two extreme information-sharing arrangements: either industry-wide complete information pooling or no information sharing at all, as in Shapiro (1986) and Li (1985). We show that these all-or-none scenarios for information sharing can be considered as two special cases of our model, corresponding to $k=n$ and $k=1$, respectively. In contrast, our model shows a very different result, namely, not all the firms in the industry would prefer to join the exchange. Firms with heterogeneous costs have different incentives for information exchange. Generally speaking, it would not be the case that all firms find beneficial to join the exchange.

There are other differences as well. For example, Shapiro (1986) considered homogeneous products ($\theta=1$). As a result, information pooling always hurts consumers in his model as well as that of Li (1985), which did not reveal the possibility that information pooling could even be beneficial to consumers in certain situations. This has different implications to the desirability of information exchange.

Finally, the current chapter is an extension to Zhu (2004). While it follows a similar model setup and methodology, there are key distinctions. The current chapter uses a more general demand function, as defined in (1), and extends the Zhu (2004) model to include broader welfare effects. On the other hand, Zhu (2004) considers both quantity competition and price competition, while this current paper considers quantity competition only.
Conclusions

What have we learned about the welfare implications of information transparency? We have found that information transparency affects producers and consumers differently. Although information transparency on the B2B exchange is socially desirable, its private desirability is deeply divided between producers and consumers, and even among producers themselves. Our model shows a conflict between producers’ and consumers’ interests regarding information transparency of the B2B exchange. Producer surplus may rise because the interaction effect and allocation effect together tend to dominate the variation effect. Concerning the consumer side, there is no allocation effect present, but the interaction effect is operating against the variation effect. Depending which effect dominates, consumers may benefit in some situations but may get hurt in other situations.

Certain types of companies (for example, high-cost suppliers of substitute products) will lack the incentives to join the B2B exchange as information transparency hurts more than helps them. In contrast to the widely held belief about its benefits (the so-called information transparency hypothesis), information transparency is indeed a double-edged sword. Our results suggest that the actual effects will be rather complicated—a transparent environment is not necessarily a good thing for all participants. This may partially explain the difficulty of most public B2B exchanges in signing up suppliers (Harris, 2001), and the recent observation that many firms switch from public exchanges to private exchanges (Hoffman et al., 2002), which tend to be less transparent than the public exchanges. For example, Wal-Mart, Cisco, Dell, and Hewlett-Packard have established private exchanges with their suppliers and business partners (Dai & Kauffman, 2002).

Our analysis shows that the welfare effects can be decomposed into two distinct effects—the variation effect on the revenue side and the allocation effect on the cost side. We found that dividing the welfare impact into these two separate effects is quite helpful to trace out the welfare impact. By introducing these new concepts, we point out the possibility that the transparency of cost information can be either beneficial or detrimental to consumers and producers. This highlights one of the differences of our model from the literature.
Thus this chapter provides a theoretical interpretation about the informational effects of B2B exchanges. On the other hand, one has to be careful when linking these results to real-world B2B exchanges. There are many reasons for firms to join a B2B exchange. The informational effects are just one, albeit an important one, of these many factors. Our model focuses on just one aspect of the informational effects induced by the B2B exchange — information transparency about costs. So the propositions and conclusions about welfare effects must be conditioned on this partial-equilibrium setting and the standard ceteris peribus assumptions under which they have been derived.

This paper can be extended in several directions. Informational effects can be multi-dimensional. We only modeled the horizontal information effects among competitors. We have not considered vertical information exchange between suppliers and manufacturers in a more general supply chain collaboration environment (Lee & Whang, 2000; Plice, Gurbaxani, & Zhu 2003). Many of these issues, especially information transparency in online supply chain collaboration, deserve further research. Second, an extension of the current model might consider double-sided externalities in a neutral marketplace, where the buyer side and seller side influence each other. Third, it might be interesting to consider firms’ participation in multiple exchanges (Belleflamme, 1998). This is another fertile area for further research. We hope that the initial work presented in this chapter will motivate other researchers to build more sophisticated models and further examine the multiple dimensions of informational effects associated with electronic markets.

References


### Endnotes

1. We cite several B2B exchanges throughout this chapter just to illustrate our points, rather than advocating or criticizing these exchanges. They were in existence at the time of writing of this work, but some of them might go out of business in the future, partly due to the transparency issues identified in this research.

2. Cost transparency is increasing on all sorts of electronic markets. On eBay, data about bidding prices, quantity, winning bids, and seller identity are all visible on its auction Web site, which started as a business-to-consumer market but also conducts business-to-business transactions as small- and medium-sized companies turn to eBay for procurement. As yet another example from our daily life, detailed breakdowns of invoice prices of new cars are now readily available on the Internet; car dealers are no longer able to hide their cost data.


4. Uncertainty about *costs* is different from uncertainty about *demand*. Cost is a technology-based, firm-specific *private* parameter, while demand is a parameter *common* to all market participants. From a modeling perspective, the distinction lies in the source of stochastic disturbance. In the case of demand, all the firms face a common disturbance in their demand functions. In the case of cost, there are as many sources of idiosyncratic disturbances as the number of firms, with each source being associated with one firm.

In order to isolate the informational role of B2B exchange, we assume that there is no other credible channel for rivals to exchange cost data. For example, unilateral announcement would not be credible and hence cannot serve as an information exchange mechanism. To avoid further complication, we assume there is only one B2B exchange in this industry and firms operate in one market only. For simplicity, we ignore the cost of joining the B2B exchange.

If products are substitutes (that is, $\theta > 0$), then firms’ reaction curves are negatively sloping, so that the covariance of any two outputs must be negative (i.e., $Cov(q_i, q_j) < 0$ for $i \neq j$). On the other hand, if products are complements, namely $\theta < 0$, then firms’ reaction curves are positively sloping, therefore $Cov(q_i, q_j) > 0$. 