

# **Effect of Information Revelation Policies on a Web-Services Marketplace**

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## Abstract

Competitive information revealed in a marketplace will have significant impact on the learning ability of the participating sellers across market sessions and therefore, on performance of the marketplace. The marketplace that we study in this paper has the following characteristics: a) Products transacted are custom-built – created specifically for a consumer and cannot be resold to other consumers b) Sellers are the bidders who have ex-ante uncertainty about the *topography* of the marketplace – whether the marketplace is a monopoly, a duopoly or how many sellers participate in a competitive market. c) Sellers have substantial ex-ante uncertainty about the quality of their product because these are custom-built. d) Sellers incur non-negligible marginal cost for building and delivering the product. In this paper, we use a computational test-bed to analyze the effect of information revelation policy on the following metrics: consumer surplus, producer surplus and social welfare. The information settings that we study are: a) Zero-Information Setting in which each seller only knows whether it won its bid at the conclusion of each market session or not b) Quasi-Information setting in which only the winning bid is revealed to all and c) Complete-Information Setting where information about all bids are revealed with dummy identification without revealing the true identity of the bidders. Based on our results, we find the producer surplus monotonically decreases with information revealed while the consumer surplus increases. Also, the social welfare generated in the Complete-Information Setting was not significantly different from that in the Zero-Information Setting. Although one may interpret this as

information revelation aiding the transfer of surplus from the producer surplus to the consumer surplus, this is not the case and we provide explanation for this. Finally, we apply our results to a specific instance of web services marketplace – reverse-auction marketplace and provide recommendations.

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## 1. Introduction

We are interested in analyzing the impact of information revelation policies on a marketplace that has the following characteristics: a) Products transacted are custom-built – created specifically for a consumer and cannot be resold to another consumers b) Sellers are the bidders who have *ex-ante* uncertainty about the *topography* of the marketplace – whether the marketplace is a monopoly, a duopoly or how many sellers participate in a competitive market. c) Sellers have substantial *ex-ante* uncertainty about the quality of their product because these are custom-built. d) Sellers incur non-negligible marginal cost for building and delivering the product.

The characteristics mentioned above can be observed in a marketplace where software vendors bid for software projects by quoting a price and promising a certain quality level for software built according to the consumers' specification (e.g. <http://www.eLance.com> and <http://www.flashline.com>). These characteristics are also observed in nascent web services marketplaces that leverage the capabilities of the web services architecture (e.g. .NET, e-speak, Sun One) to create dynamic loosely coupled systems, which can be dynamically discovered and bundled at run time (Developer Works 2000).

There are several questions that need to be addressed when creating such marketplaces. Some of the questions that have already been addressed are: what pricing strategy should sellers adopt when demand for their product is unknown (Greenwald and Kephart 1999), how should sellers bundle goods and how should they price competitive bundles (Bakos

and Brynjolfsson 1999), how sellers identify niches and price their products (Brooks, Durfee and Das, 2000). In this paper, we focus on the information revelation policy (a complete literature review is available in section 2). In a marketplace with repeated interactions among the competing sellers, when bids are revealed according to the information revelation policy adopted, the competing sellers will have opportunities to learn about their competition and compete intelligently in future. The information revealed and in turn, the “learning” affects the consumer surplus, producer surplus and social welfare<sup>1</sup> generated, parameters that we use to compare the different information revelation policies. The policies compared in this paper are explained later in this section. We study the impact of information revelation policies using a computational web services marketplace for predictive model building (Arora et al. 2001). We do so for several reasons. First, the marketplace is representative of nascent web service marketplaces in terms of the structure and interactions among the players. Second, predictive models – products transacted in the marketplace – have an objective measure of quality, an important determinant of consumer utility. The marketplace works as follows.

A consumer creates a request in the marketplace for a predictive model and this initiates a *market session*<sup>2</sup>. The marketplace features sellers with different machine-learning techniques to build predictive models. Each seller responds to the consumer request by

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<sup>1</sup> Social welfare = consumer surplus + producer surplus + broker profits

submitting a price-quality pair (also referred to as an *SLA* which stands for *Service Level Agreement*), thereby promising certain level of consumer surplus. After receiving the *SLAs*, the consumer chooses the seller promising the highest consumer surplus as the winner. The winner bears the risk due to ex-ante uncertainty and delivers the promised consumer surplus<sup>3</sup>; this is explained later in section 3. The decision problem for the seller is to determine the optimal *SLA* to bid based on the information available from previous market sessions. The extent of information revealed determines the extent to which uncertainty is reduced and therefore, the optimality of seller's decision. Examples of the different information revelation policies can be borrowed from traditional marketplaces. In municipal construction auctions, bid information about all bidders, including the identity of the bidders, is released. In other typical auctions, only the winning bid information is released. In this paper, we define and compare the following information revelation policies (also referred to as *information environments*):

- a) Quasi-Information Setting: information released in this setting is similar to a typical auction setting. Only the winning *SLA* information is released. Losing sellers learn about the *SLA* submitted by the winner (the identity of the winner is not revealed), whereas, the winner does not learn the *topography* of the marketplace.

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<sup>2</sup> Market Session refers to the period of one complete transaction starting from when consumer submits the request for product, to the point when the product/service is developed and delivered to the consumer.

<sup>3</sup> This is similar to a first-price sealed bid auction where the winner delivers the promised level. Its equivalent second-price sealed bid mechanism would be for the seller to deliver the consumer surplus at the level promised by the first loser. In a web-services marketplace, the number of competitors may not be known ex-ante; based on the result from McAfee and McMillan (1987) that shows that a first-price sealed

- b) **Complete-Information Setting:** This is similar to the information revelation policy followed in the municipal construction contract auctions where all bids with the identity of the bidders are released. We model a similar setting to analyze the non-collusive learning behavior of the sellers. To prevent collusive behavior, bids are released with bidders' dummy names and not their real names. To a particular seller, the information revealed provides details about the *topography* of the marketplace and *SLAs* submitted by its competitors but the not the true identity of its competitors.
- c) **Zero-Information Setting:** In this setting, only the outcome – win or loss – of its participation in the market session is known. Sellers learn neither about the topography of the marketplace nor the bids of their competitors.

Sellers ex-post knowledge	Zero-Information Setting	Quasi-Information Setting	Complete-Information Setting
Outcome of its participation – win or lose	Yes	Yes	Yes
Winner's <i>SLA</i>	-	Yes	Yes
Winner's identity	-	-	Yes
Knowledge about presence of competition	Only to the losing sellers	Only to the losing sellers	Yes
<i>SLAs</i> of all sellers	-	-	Yes
Number of participating sellers	-	-	Yes
True identities of all sellers	-	-	-

Table 1: Ex-post information made available at the conclusion of each market session.

Table 1 summarizes the information made available under each setting at the conclusion of each market session. Note that the ex-post information is useful only for learning

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bid mechanism generates maximum profits for the auctioneer when the number of competitors is not known to the participating bidders. Therefore, we employ a first-price sealed bid mechanism.

purposes. The information environments are different in terms of how the *topography* of the marketplace is revealed. Winning sellers in both the Zero and the Quasi-Information settings, are not aware of the presence or absence of competitors in the marketplace. However, the losing sellers in both the Zero and the Quasi-Information Settings learn about the presence of competition. In addition, the sellers in the Quasi-Information Setting also know the details of the *SLA* submitted by the winner. Finally, in complete-Information setting, the number of participating sellers and the *SLAs* submitted by all sellers are revealed ex-post.

The impact of the choice of information revelation policy on the performance of a marketplace has not received much attention in the auction theory literature. Our work is distinctive in its focus on learning and its impact on the performance of the marketplace. We study the non-collusive behavior of the participating sellers. Specifically, we compare the different information settings on the following metrics: consumer surplus, producer surplus and social welfare. Results from this paper can help understand the impact of choice of information setting on the performance of a web services marketplace. The paper is organized as follows: in section 2, we review the literature. Following this, section 3 motivates the problem and states the research questions addressed in this paper. Section 4 describes IBIZA-ML, multi-agent web-services marketplace. Learning methodology adopted for each information setting is explained in section 5. We present our results in Section 6 and finally we conclude in section 7.

## 2. Literature Review

In this section we review the literature on the value of information studied under different marketplaces – marketplaces with posted price and auction-based marketplace. A considerable amount of work has been conducted on how consumers' knowledge of price information affects the performance of a competitive marketplace. Theoretical models show that when consumers possess complete knowledge of price information, firms charge lower prices. A classical work is the Bertrand model of competition (Bertrand 1883): When identical goods are sold and the consumers are aware of prices charged by all firms, then price charged by all firms falls to the marginal cost of the good. This occurs only under constraints of constant marginal costs and unlimited capacity. With capacity constraints, the Bertrand model corresponds to the Cournot model (Kreps and Scheinkman 1983). Another related work by Stigler (1961) shows that advertising – information dissemination – causes both price and price dispersion to decrease. Empirical studies on retail stores by Devine and Marion (1972) and on the market for eyeglasses and optometry services conducted by Kowka (1984) have tested and validated this. But when consumers possess imperfect knowledge, a theoretical model developed by Pratt et al. (1979) shows that at equilibrium, prices differ substantially from seller-to-seller. A similar work by Varian (1980) also shows that price or price dispersion does

not lower with information dissemination when consumers have differential cost of acquiring information<sup>4</sup>.

The role of information is also relevant in a multi-object sequential auction where there is room for a bidder to learn about other bidders. Weber (1982) developed a theoretical model that shows that if the valuations are correlated among the sellers, the expected bid-price rises because early auction rounds provide information about the value of the good. Contrary to the model's prediction, prices in multi-unit repeated auctions of wine did not increase, (Ashenfelter 1989). McAfee and Vincent (1993) and Bernhardt and Scoones (1994) developed analytical models to explain this anomaly. Neither model provides any intuition on how information gained across the sequence of auctions decreases prices. The analytic model by Bernhardt and Scoones (1994) is consistent with real-world observations. Their solution relies on two primary assumptions: one, that products are homogenous across auctions and two, that the utility from winning the second auction after winning the first auction is zero and therefore, winners from the first auction never participate in the second auction. Neither of these assumptions is valid in a web services marketplace. While the utility (or profit perceived by the bidder who is the seller in our case) not only varies across the auctions, so does ex-ante uncertainty about quality and therefore, about revenue and profits exist. These violate the first assumption. The second assumption is also violated since bidders – sellers – continue to participate in all

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<sup>4</sup> This paper does not analyze the impact of consumer's knowledge in the marketplace but rather addresses the impact of sellers' perception of other sellers.

future auctions even if they win any previous auction. Therefore, results from these models cannot be applied to our framework.

Thomas (1996) models the information revelation policy and provides a game-theoretic model. Thomas (1996) finds that as information revealed in the marketplace increases, competition increases and expected seller profit decreases. The analysis assumes that sellers are aware of the topography of the marketplace and are certain about their expected profits ahead of participation. Again, neither of these two assumptions applies to our framework. In the following section we further motivate the problem and provide motivation for the computational methodology that we adopt.

### **3. Motivation**

In the earlier section, we mentioned certain limitations due to the assumptions in prior work in this area. In this section, we relax the assumptions and develop game-theoretic models to determine strategy outcomes under different settings. In the first sub-section, sellers have ex-ante uncertainty about their product quality but aware of the topography of the marketplace. In the second sub-section, sellers have ex-ante uncertainty both about their product quality and about the topography of the marketplace. The purpose of this section is to present a case for a computational approach based on the intractability of solving such game-theoretic models. The following paragraph describes the game-theoretic set-up.

Sellers can choose either  $(P_L, Q_L)$  or  $(P_H, Q_H)$  when choosing a price-quality

pair to bid as their *SLA*. The price-quality pairs are related in the following manner: price level  $P_H > P_L$  and similarly quality level  $Q_H > Q_L$ . If  $Q_{promised}$  is the quality promised and  $P_{promised}$  is the price promised, then, the consumer surplus promised is given by  $Q_{promised} - P_{promised}$ . Between the two price-quality pairs bid as *SLA*, for the sake of simplicity that a high-quality product at a higher price generates higher consumer surplus than a low-quality product at a lower price i.e.,  $(Q_H - P_H) > (Q_L - P_L) > 0$ . After receiving bids from all sellers, the consumer compares and selects the seller that promises the highest consumer surplus.

In this marketplace, each seller employs one machine-learning technique to build predictive models and is not permitted to replace the technique. Therefore, a seller's *ex-post* quality is a characteristic of its technique and, in our model, it is determined by nature and not by the seller. If the actual quality,  $Q_{actual}$ , differs from the promised quality,  $Q_{promised}$ , the seller is either penalized or rewarded with a bonus. The penalty  $\Delta = Q_{promised} - Q_{actual}$  becomes the bonus when  $\Delta < 0$ . In the next sub-section we derive equilibrium bidding strategies for a seller, which is aware of the monopolistic nature of the marketplace.

### **3.1 Monopolistic Marketplace:**

The participating seller knows the topography of the marketplace. Its ex-ante quality uncertainty is modeled by allowing nature to determine the product quality as either  $Q_L$

with probability  $I$  or  $Q_H > Q_L$  with probability  $1-I$ . The seller is not aware of nature's action and chooses to submit one of the two possible *SLAs*. The extensive form in figure 1 shows the payoffs.

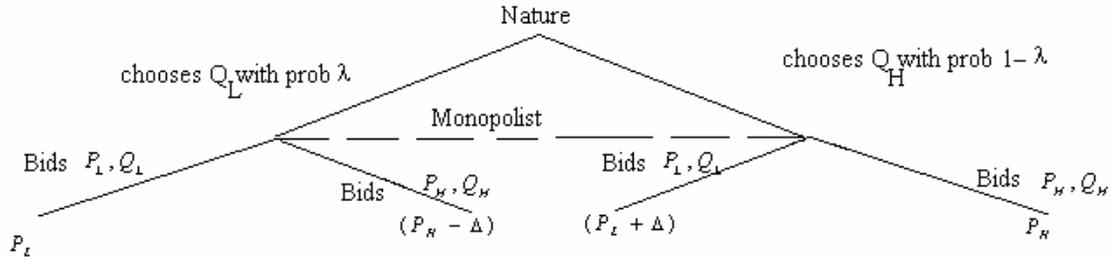


Figure 1: Extensive form for the monopolistic game.

The expected payoff from bidding  $(P_H, Q_H)$  is  $(P_H - \Delta) * I + P_H * (1-I)$  and from  $(P_L, Q_L)$  is  $P_L * I + (P_L + \Delta) * (1-I)$ . Using the condition  $(Q_H - P_H) > (Q_L - P_L)$ , or  $\Delta = (Q_H - Q_L) > (P_H - P_L)$ , it is easy to show that the *SLA* pair  $(P_L, Q_L)$  generates the highest expected payoff for the monopolist and therefore, it is the dominant strategy. The expected profit for the monopolist is  $\Pi_{monopoly}^{w/inf} = (P_L + \Delta * (1-I))$ . Consumer Surplus is  $CS_{monopoly}^{w/inf} = (Q_L - P_L)$  Note that this *SLA* is also the least preferred *SLA* from the consumer's perspective.

### 3.2 Duopoly

Consider a duopoly marketplace where the two sellers differ only in the probability with which nature chooses  $Q_L$ . Let this probability be  $I_1$  for seller-1 and  $I_2$  for seller-2.

We assume that both sellers know both probability values. Similar to the monopoly case,

each seller bids one of the two price-quality pairs but only the seller that offers the highest consumer surplus wins. When both sellers promise the same consumer surplus, the tie is broken by randomly choosing one seller. Expected rewards are shown in the extensive form in figure 2.

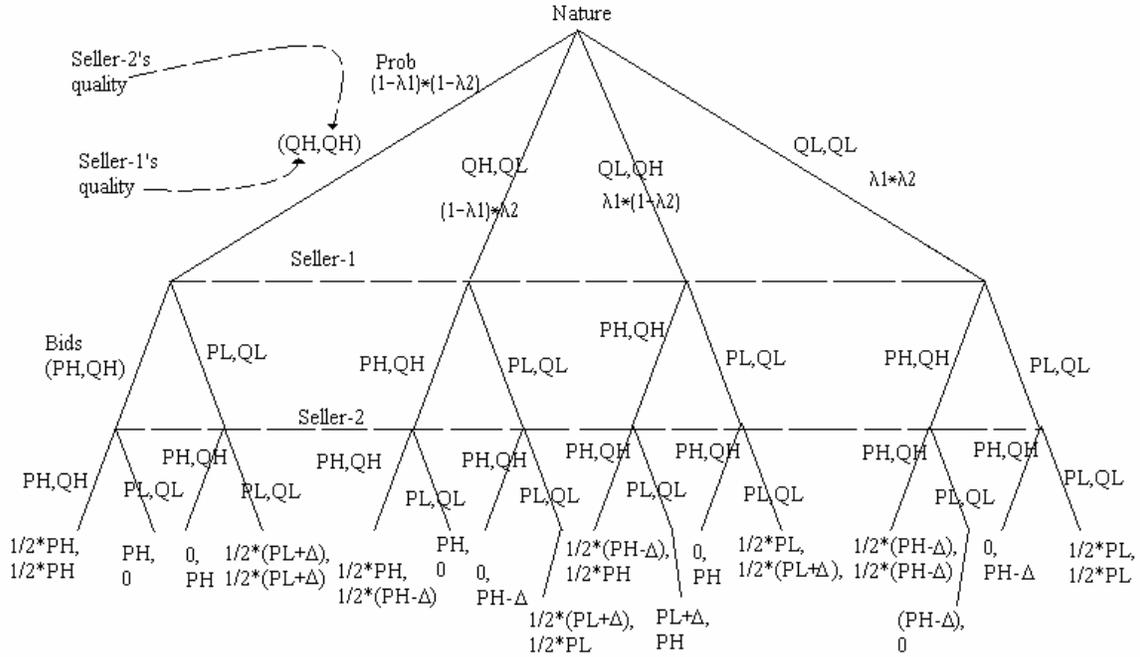


Figure 2: Extensive form of a single period duopoly game

The mixed strategy Nash-equilibrium (see appendix) is for seller-1 to bid the *SLA* pair  $(P_L, Q_L)$  with a probability of  $\mathbf{a}_1^{w/inf} = (P_H - \Delta * I_2) / (\Delta - (P_H - P_L))$  and the *SLA* pair  $(P_H, Q_H)$  with a probability of  $1 - \mathbf{a}_1^{w/inf}$ . Mixed-strategy equilibrium exists only for condition  $\Delta < 2 * P_H - P_L$ , otherwise only the pure strategy exists and it is optimal for seller-1 to always bid  $(P_H, Q_H)$ . For seller-2 these are symmetrical. Also, note that a seller's probability of choosing a bid is dependent on the probability of its opponent's  $I$  -

uncertainty about opponent's product quality. The expected profit for seller-1 is given

by  $\Pi_{duopoly-1}^{w/inf} = (P_H - \Delta * I_2) * (P_L + \Delta * (1 - I_2)) / (2 * (\Delta - (P_H - P_L)))$ . This can be

rewritten as  $\Pi_{duopoly-1}^{w/inf} = \mathbf{a}_1^{w/inf} * \Pi_{monopoly-2}^{w/inf} / 2$ . Therefore, seller-1's duopoly profit is

lower than its opponent's monopoly profit by a factor of  $\mathbf{a}_1^{w/inf} / 2$ . The expected

consumer surplus generated in duopoly,  $CS_{duopoly}^{w/inf}$ , is

$$\frac{(P_L * (Q_H - P_H) - Q_H * P_H + \Delta * (Q_H - P_H - I_1 * (I_2 * Q_H - P_H)) + I_2 * (I_1 * Q_L + P_H))}{(\Delta - (P_H - P_L))}$$

This can also be rewritten as  $CS_{duopoly}^{w/inf} = CS_{monopoly}^{w/inf} + (1 - (\mathbf{a}_1^{w/inf} * \mathbf{a}_2^{w/inf})) * (\Delta - (P_H - P_L))$ .

We find that consumer surplus generated is better in the duopoly than in the monopoly.

### 3.3 Uncertain about the Topography

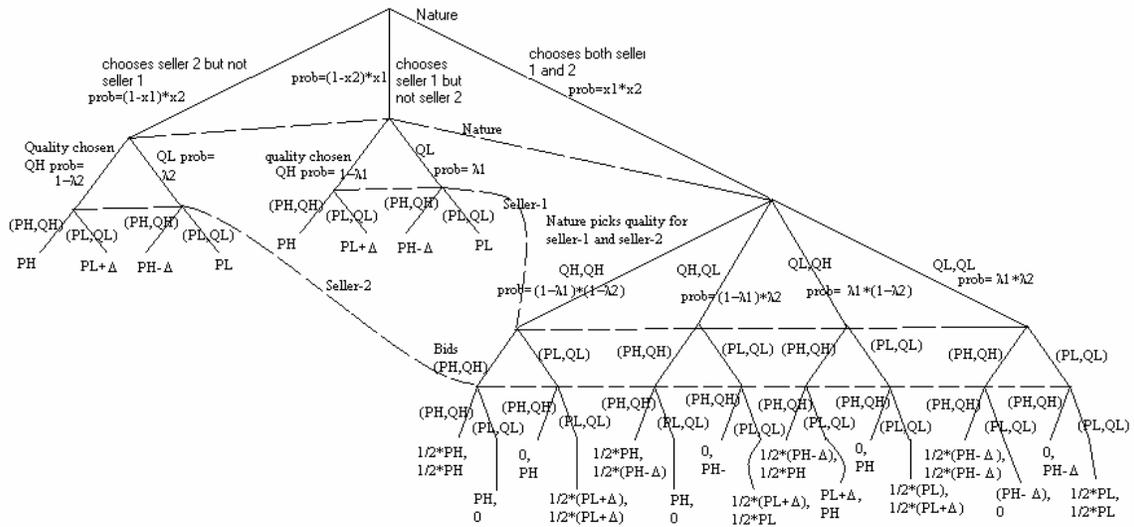


Figure 3. Uncertain about topography

In this section, we deal with a setting where sellers are not aware of the topography of the

marketplace. We model seller's uncertainty of the topography in the following manner: nature determines each seller's participation with a certain probability. This probability is  $X_1$  for seller-1 and  $X_2$  for seller-2. This means that the marketplace is in duopoly with a probability of  $X_1 * X_2$ . With a probability of  $(1 - X_1) * (1 - X_2)$ , no seller is selected to participate. At the point of bidding, each seller knows if it is selected to participate, but it is not aware of its opponent's participation. This game and the payoffs are shown in the extensive form in figure 3. The last branch of nature's move corresponds to duopoly and the other two branches correspond to monopoly. The setting with no seller participating is not shown in the figure.

Mixed strategy Nash-equilibrium (see appendix) for seller-1 is to bid the *SLA* pair  $(P_L, Q_L)$  with a probability of  $\mathbf{a}_1^{wo/inf} = 2 - (2/X_1) + (P_H - \Delta * I 2) / (\Delta - (P_H - P_L))$  and the *SLA* pair  $(P_H, Q_H)$  with a probability of  $1 - \mathbf{a}_1^{wo/inf}$ .  $1 \geq \mathbf{a}_1^{wo/inf} \geq 0$  implies that the equilibrium in mixed strategy is valid only for

$$2 / (1 + (P_H - \Delta * I 2) / (\Delta - (P_H - P_L))) > X_1 > 1 / (1 + (P_H - \Delta * I 2) / (2 * (\Delta - (P_H - P_L)))) .$$

For  $X_1 \rightarrow 0$ , it is intuitive that seller-2 always bids  $(P_L, Q_L)$ , regardless of  $\mathbf{a}_1^{wo/inf}$ . But as  $X_1 \rightarrow 1$ , seller-1 bids  $(P_L, Q_L)$  with probability  $\mathbf{a}_1^{wo/inf} = \mathbf{a}_1^{w/inf}$ . Again mixed strategy exists only when  $\Delta < 2 * P_H - P_L$  and otherwise, seller-1 plays a pure strategy of bidding  $(P_H, Q_H)$ . Seller-2's probability of bidding  $(P_L, Q_L)$ ,  $\mathbf{a}_2^{wo/inf}$ , symmetrical to  $\mathbf{a}_1^{wo/inf}$ . Further, note that a seller's probability of choosing a bid-pair is dependent on its opponent's  $I$  - uncertainty about opponent's product quality. Using this we

calculate the expected profit for seller-1 as

$$\Pi_1^{wo/inf} = (P_H - \Delta * I_2) * (P_L + \Delta * (1 - I_2)) * X_1 * X_2 / (2 * (\Delta - (P_H - P_L))).$$

Comparing it to the case where sellers are aware of the topography to be duopoly, we

find that the expected profit,  $\Pi_1^{wo/inf} = \Pi_{duopoly-1}^{w/inf} * X_1 * X_2$ . As  $X_1, X_2 \rightarrow 1$  i.e., both

sellers are always chosen,  $\Pi_1^{wo/inf} \rightarrow \Pi_{duopoly-1}^{w/inf}$ . Similarly comparing this to the

monopoly- full information case,

$$\Pi_1^{wo/inf} = \Pi_{monopoly-2}^{w/inf} * X_1 * X_2 * (P_H - \Delta * I_2) / (2 * (\Delta - (P_H - P_L))).$$

The consumer surplus generated is

$$CS^{wo/inf} = ((1 - I_2) * Q_H + I_2 * Q_L) * (1 - X_2) * X_1 + ((1 - I_1) * Q_H + I_1 * Q_L) * (1 - X_1) * X_2 \\ + \frac{(P_L * (Q_H - P_H) - Q_H * P_H + \Delta * (Q_H - P_H - I_1 * (I_2 * Q_H - P_H) + I_2 * (I_1 * Q_L + P_H)))}{(\Delta - (P_H - P_L))}$$

or

$$CS^{wo/inf} = ((1 - I_2) * Q_H + I_2 * Q_L) * (1 - X_2) * X_1 + \\ ((1 - I_1) * Q_H + I_1 * Q_L) * (1 - X_1) * X_2 + CS_{duopoly}^{w/inf}.$$

$$CS^{wo/inf} = ((1 - I_2) * Q_H + I_2 * Q_L) * (1 - X_2) * X_1 + \\ Or \quad ((1 - I_1) * Q_H + I_1 * Q_L) * (1 - X_1) * X_2 + \\ CS_{monopoly}^{w/inf} + (1 - ((P_H - \Delta * I_2) * (P_H - \Delta * I_1) / (\Delta - (P_H - P_L)))^2) * (\Delta - (P_H - P_L))$$

As  $X_1, X_2 \rightarrow 1$  i.e., both sellers are always chosen,  $CS_{duopoly}^{wo/inf} \rightarrow CS_{duopoly}^{w/inf}$ . But when either

$X_1$  or  $X_2$  is zero, a monopolistic condition arises and consumer surplus is minimal.

### 3.4 Discussion

In the earlier section we compared the seller profits and the consumer surplus generated in the marketplace. In this section, we are interested in comparing the effect of information on the bidding behavior. For the sake of exposition, we let us define *aggression* as the probability of bidding  $(P_H, Q_H)$ . A seller agent is more aggressive in one setting if probability of bidding  $(P_H, Q_H)$  in that setting is higher than the probability of bidding  $(P_H, Q_H)$  in another setting. In the Zero-Information Setting (sellers are uncertain about topography), seller-1's probability of bidding  $(P_H, Q_H)$  is  $X_1 * (1 - \mathbf{a}_1^{wo/inf})$  and seller-1's probability of bidding  $(P_L, Q_L)$  is  $X_1 * \mathbf{a}_1^{wo/inf}$ . Similarly in the Complete-Information Setting (sellers are certain about topography) seller-1's probability of bidding  $(P_H, Q_H)$  is  $X_1 * X_2 * (1 - \mathbf{a}_1^{w/inf})$  and seller-1's probability of bidding  $(P_L, Q_L)$  is  $X_1 * (X_2 * \mathbf{a}_1^{w/inf} + (1 - X_2) * 1)$ .

Zero-Information Setting is more aggressive than the Complete-Information Setting iff  $(1 - \mathbf{a}_1^{wo/inf}) > X_2 * (1 - \mathbf{a}_1^{w/inf})$ . But we know that  $\mathbf{a}_1^{w/inf} > \mathbf{a}_1^{wo/inf}$ , since the difference  $\mathbf{a}_1^{w/inf} - \mathbf{a}_1^{wo/inf} = 2 * (1 - 1/X_1)$  is non-decreasing in  $X_1$  and its maximum value is zero when  $X_1$  ranges  $[0,1]$ . Based on this, we say that without lack of information, sellers aggressively bid offering higher consumer surplus. But this reduces the producer surplus generated in this marketplace. Social welfare comparison requires further analysis.

Social welfare generated in the Zero-Information Setting is

$$((1 - I2) * Q_H + I2 * Q_L) * (1 - X_2) * X_1 +$$

$$((1 - I1) * Q_H + I1 * Q_L) * (1 - X_1) * X_2 + CS_{duopoly}^{w/inf} + (\Pi_{duopoly-1}^{w/inf} + \Pi_{duopoly-2}^{w/inf}) * X_1 * X_2$$

Similarly social welfare generated in the Complete-Information Setting is:

$$CS_{duopoly}^{w/inf} * X_1 * X_2 + CS_{monopoly}^{w/inf} * (1 - X_1) * X_2 + CS_{monopoly}^{w/inf} * X_1 * (1 - X_2) + (\Pi_{duopoly-1}^{w/inf}$$

$$+ \Pi_{duopoly-2}^{w/inf}) * X_1 * X_2 + \Pi_{monopoly-2}^{w/inf} * (1 - X_1) * X_2 + \Pi_{monopoly-2}^{w/inf} * X_1 * (1 - X_2)$$

Simplifying the equations and substituting values from the previous sections, we can see that the Zero-Information setting generates higher social welfare under the condition,

$$Q_L - P_L + (1 - ((P_H - \Delta * I2) * (P_H - \Delta * I1) / (\Delta - (P_H - P_L)))^2) * (\Delta - (P_H - P_L)) -$$

$$\Delta * (I2 - I1) * (X_1 - X_2) / (1 - X_1 * X_2) > 0$$

When  $X_1, X_2 \rightarrow 1$ , and that is when social welfare generated in the two settings is same.

Under monopolistic condition, say  $X_1 \rightarrow 0$   $X_2 \rightarrow 1$  social welfare generated in the Zero-

Information is  $(Q_H - I1 * \Delta) + CS_{duopoly}^{w/inf}$  and social welfare generated in the Complete-

Information Setting is  $(Q_L + \Delta(1 - I2))$ . Zero Information Setting generates higher

social welfare if,  $(Q_H - I1 * \Delta) + CS_{duopoly}^{w/inf} > Q_L + (1 - I2) * \Delta$ . Substituting for  $CS_{duopoly}^{w/inf}$ ,

we get  $(Q_L - P_L) + (1 - (a_1^{w/inf} * a_2^{w/inf})) * (\Delta - (P_H - P_L) + \Delta(I2 - I1)) > 0$ . If we assume

that seller with higher quality has higher probability of getting selected, the left hand side

is non-zero and, the Zero-Information Setting generates higher social welfare than the

Complete-Information Setting.

The analytical models demonstrate the equilibrium strategies both when sellers know the

topography of the marketplace – monopoly or a duopoly – and when sellers are not aware of the topography. We also show that the producer surplus decreases while consumer surplus increases with increase in uncertainty. To derive equilibrium strategies, our static model assumes that each seller knows its probability of participation ( $X_1$  for seller-1 and  $X_2$  for seller-2), which is a fixed value. In reality, the probability values are not fixed and are, in fact, correlated across market-sessions. Further, one can expect the seller, which wins more number of market sessions, to have a higher probability value than a losing seller. Therefore, an appropriate model has to take into account the actions taken, information obtained and the resulting changes in the probability values. Analytical models cannot be extended to this dynamic multi-period problem, and therefore, we need a computational approach.

In our computational approach we test the following hypotheses that were obtained from the static models analyzed in sections 3.1, 3.2 and 3.3.

1. Consumer surplus is higher in environments where lesser information is revealed.

Hence we expect the following order of the information revelation policies from higher consumer surplus to lower consumer surplus: *Complete-Information Setting* < *Quasi-Information Setting* < *Zero-Information Setting*.

2. Producer surplus is higher in environments where more information is revealed.

Hence we expect the following order of the information revelation policies from higher producer surplus to lower producer surplus: *Complete-Information Setting* >

*Quasi-Information Setting > Zero-Information Setting.*

3. The Zero-Information Setting delivers higher social welfare than the Complete-Information Setting.

To answer our research questions, we use a computational approach. Software agents in our set-up use reinforcement learning-techniques to mimic sellers' learning. Our computational set-up differs from the game theoretic model in that sellers in our set-up hold a cash position and incur an *SLA*-processing fee while participating in market sessions. Profits generated across market sessions increase the cash position while losing market sessions deplete the cash position. If a seller's cash position falls to zero, then the seller is evicted from the marketplace. The following section describes the marketplace.

#### 4. IBIZA-ML: A Web-Services Marketplace for Machine Learning Services

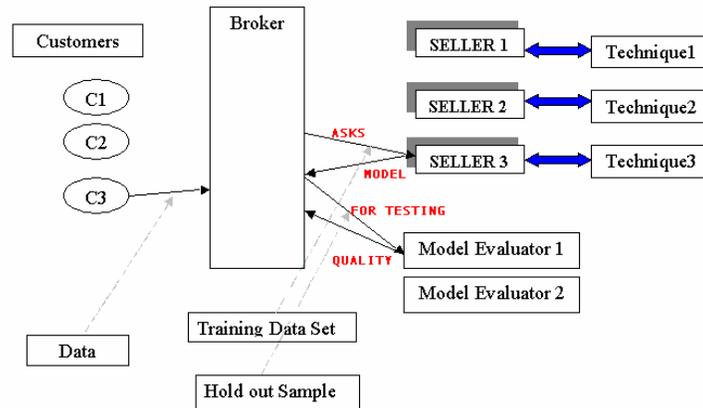


Figure 4. An IBIZA web services market for custom model development

Our marketplace, IBIZA-ML<sup>5</sup>, features seller-agents that offer machine-learning capabilities as a web service; products that are transacted are predictive models built according to consumer-requests. Figure 4 shows the schematic diagram of the marketplace. There are four types of agents in IBIZA-ML: the buyer, the broker, seller-agents and model evaluators. The buyer has a dataset and would like to buy a predictive model built using his dataset that offers him the highest consumer surplus. The seller-agents have assets (the machine learning methods) that can be used to build models using the buyer's data. When the marketplace is initiated, each seller-agent is endowed with  $M$  dollars to defray costs incurred while participating in market sessions.

At the start of the market session, sellers promise a certain level of consumer-surplus. Sellers need to decide on the level of consumer surplus and, specifically, which price-quality pair to submit as *SLA*. Their decision-choice is based on the environment modeled as a Markov Decision Process (MDP), and information revealed at the end of each market session is used to update this MDP (section 5 describes the MDP in detail). After receiving the *SLAs* from all sellers, the broker declares a winner – the seller that promises the highest consumer surplus. The winner builds the product. Once the product is built, a model evaluator assesses the quality of the model against a hold out sample. The actual quality of a model is the number of correct predictions made on the hold out sample expressed as a percentage. The following subsections will detail the sequence of interactions among the agents.

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<sup>5</sup> IBIZA-ML was implemented using e-speak, the e-services architecture and technology from HP.

#### 4.1 Interactions between the Consumer and the Broker

The consumer submits the following information as a part of a RFQ (Request for Quote) to the broker:

- The training and evaluation data sets.
- Meta data associated with data set giving information about the types and value ranges of variables.
- The time window (deadline) within which the model is to be developed.

#### 4.2 Interaction between the Broker and the Sellers

On receiving the request from the consumer, the broker initiates the market-session. The broker advertises parts of the consumer-request – meta-data associated with the dataset and time window for developing and delivering the model – to the seller-agents and solicits *SLA* quotes from the seller-agents. Seller-agents submitting *SLAs* incur an *SLA*-processing fee  $P_b$ . *SLA* submitted by a seller-agent  $i$  includes a promised quality  $Q_i^p$  and a price  $0 \leq P_i \leq Q_i^p$ . Since quality is expressed as a percentage,  $0 \leq Q_i^p \leq 100$ .

Consumers accept *SLAs* so long as they generate non-negative consumer surplus, given

$$\text{by } CS = [Q_i^p - P_i] \dots \dots (1)$$

After receiving *SLAs* from all participating seller-agents, the broker compares them and chooses the seller-agent that promises the highest consumer surplus as the winner. If

two sellers promise the same consumer surplus level, the seller promising higher quality is chosen. If the qualities promised are also same, then the tie is broken by randomly choosing one seller-agent. The winning seller is provided with the training dataset and it then uses its machine-learning method to build a predictive model for the dataset provided by the consumer. Since sellers use different predictive-model building techniques, their actual quality as evaluated by the evaluation agent differs. Recall that actual quality is the number of correct predictions made by the model on the hold out sample, expressed as a percentage. Depending on whether the actual quality,  $Q_i$ , is lesser than or greater than the promised quality,  $Q_i^p$ , the seller-agent  $i$  obtains a bonus or pays a penalty  $\Delta = (Q_i^p - Q_i)$ . The symmetric nature of the penalty ensures incentive compatibility. To see that, let us define the profit function for a seller.

The revenue generated for the winner is  $P_i$ . We assume that the market for computing is competitive, the cost incurred – the cost of computing – is calculated as  $MC_{time} * t_i$  where  $t_i$  is the total time taken to decide about the bid, build the model and evaluate the model and  $MC_{time}$  \$/millisecond is the marginal cost of computing. Note that all sellers incur the decision-making cost while the winning seller incurs all three costs – decision-making cost, model-building cost and model-evaluation cost. The profit generated is therefore  $P_i - \Delta - MC_{time} * t_i - P_b$ . Expanding and rewriting this based on equation 1, the profit generated by the winning seller is  $Q_i - CS - MC_{time} * t_i - P_b$ . Observe that the expected profit is not dependent on the promised quality but instead on the consumer surplus

promised. This allows us to simplify our setting such that the sellers submit their true expected quality and use price as a tool to alter the consumer surplus promised. This means that in expected terms  $\Delta = 0$  and therefore, the expected profit can be rewritten as  $P_i - MC_{time} * t_i - P_b$ . This profit increases the cash position of the seller-agent. Seller-agents submitting *SLAs* that did not win incur a loss equal to the *SLA*-processing fee,  $P_b$ , paid to the broker and the decision-making cost. This loss is paid from the cash-position held and if a seller-agent loses all its money in the initial endowment, it is evicted from the marketplace. At the end of the market session, it is this *SLA information* – price and quality promised (not the actual quality) – that the broker disseminates depending on the *information environment* adopted.

## 5. Learning Techniques and Information Environment

As long as sellers remain in the marketplace, they participate by promising an *SLA*<sup>6</sup>.

Each seller-agent optimizes the profit function  $\max_{P_i} \{g_{win}^{P_i} * (P_i - MC_{time} * t_i) - P_b\}$  where

$g_{win}^{P_i}$  represents the probability of winning at price  $P_i | Q_i^P, t_i$ . Note that a seller's bid is accepted only if the consumer surplus is non-negative i.e.,  $Q_i^P > P_i$ . When participating in the market-sessions, seller-agents *learn* about their model building capabilities –

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<sup>6</sup> This assumption ensures that sellers do not prolong their survival in the marketplace without active participation. This assumption is needed for analyzing the market topography dynamics and the responses which otherwise would be impossible.

quality and cost – and submit their expected quality; also, they learn to *select* an optimal *SLA* price. The following subsections describe the techniques adopted.

## 5.1 Learning Quality and Cost

Recall that cost is a linear function of the time taken to build. Prior to submitting an *SLA*, the quality of the model and the time taken to build the model are estimated using the regression equations given below. Observe that the meta-data<sup>7</sup> associated with the consumer-request are the independent variables of the regression equation (e.g. size of the data set, number of continuous and categorical variables).

$$q_i = \mathbf{a}_{0i} * (\text{Number of Categorical Variables}) + \mathbf{a}_{1i} * (\text{Number of Continuous Variables}) \\ + \mathbf{a}_{3i} * (\text{Size of training dataset}) + \mathbf{a}_{4i} * (\text{Size of Evaluation Dataset}) + \mathbf{e}_1$$

$$t_i = \mathbf{b}_{0i} * (\text{Number of Categorical Variables}) + \mathbf{b}_{1i} * (\text{Number of Continuous Variables}) \\ + \mathbf{b}_{3i} * (\text{Size of training dataset}) + \mathbf{b}_{4i} * (\text{Size of Evaluation Dataset}) + \mathbf{e}_2$$

Observe here that a seller-agent learns about its quality only if its *SLA* is chosen as the winner. Losing seller-agents do not build the models and therefore, do not know the actual quality or the cost of building. If data points, including the actual values of quality and time, are available, one can use OLS technique to estimate the coefficients. In this setting, OLS is not desirable since the time expended in calculating the coefficients and therefore, the cost associated with it increases across market sessions. For example, time

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<sup>7</sup> If the application were different, the independent variables would meta-data associated with the RFQ submitted by the consumer

taken to compute the OLS coefficients after the 100<sup>th</sup> market session would be larger than that after the 10<sup>th</sup> market session. *Recursive Regression Technique* solves this problem and provides an incremental approach to evaluate the coefficients from their prior values and estimation errors. Results from the economic literature are presented below. For further reading refer to West and Harrison (1997).

Suppose the regression equation  $y = x^T * \mathbf{b} + \mathbf{e}$  where  $\mathbf{e} \sim N(0, \mathbf{s}^2)$ , is estimated using the recursive regression technique. Let  $x_t$  and  $y_t$  represent the independent and the dependent variables at instant  $t$ . Also, let us suffix the priors with  $t - 1$  and posteriors with  $t$ . Assuming  $\mathbf{b}$  to be a T distribution  $\mathbf{b} \sim T_{n_{t-1}}(b_{t-1}, V_t)$ , the posterior distribution of  $\mathbf{b}$  can be determined as:

$$b_t = b_{t-1} + V_{t-1} * x_t * (x_t^T * V_{t-1} * x_t + \mathbf{s}^2)^{-1} * (y_t - x_t^T * b_{t-1})$$

$$V_t = V_{t-1} + V_{t-1} * x_t * (x_t^T * V_{t-1} * x_t + \mathbf{s}^2)^{-1} * x_t^T * V_{t-1}.$$

If the parameters of the underlying process that generates the data are stable, one can expect the estimates to converge as the number of observations  $t$  increases. We use this regression technique to estimate the coefficients of both quality and time taken to build.

## 5.2 Selecting the Optimal SLA-Price

When selecting the SLA-price, the seller-agent takes into account its belief about other seller-agents in the marketplace. When there is no learning involved, the belief is not

updated. The strategies and therefore, the decisions are static and independent of the *information environment*. Arora et al. (2000) use a similar static setting to compare the performance of different market mechanisms. We described the dynamic nature of the marketplace in section 3. In each market-session, each seller has to decide the *SLA*-price to quote. Selecting a high *SLA*-price lowers the probability of winning but generates high profits if successful, while choosing a low price has high probability of winning but generates low profits. Additionally, risk-averse sellers can trade-off their short-term profits for long-term profits and avoid subsequent exit from the marketplace. The seller may even quote a price to incur a loss just so that it wins and learns about its relative performance with respect to its competitors. This information can only be obtained by participating in the marketplace and is crucial in determining its strategy; this is explained in detail in sections 5.2.2 and 5.2.3.

A seller that can perfectly estimate its product quality is not guaranteed a win for future market sessions if it resubmits a winning *SLA*. This is due to the dynamic nature of the marketplace. Furthermore, there may also be other *SLA*-prices that yield better profits. Therefore, a seller-agent has to trade-off between exploiting – quoting the same *SLA* price and receiving an estimated profit – and exploring other *SLA* prices. Exploration depends on the cash-position of the seller-agent. For example, when the cash position is low, the seller-agent explores prices that are lower than its previous *SLA*-price, and quotes prices conservatively than when the cash position is high. Apart from the cash-position, competition parameters available from the information environment also

determine the choice of *SLA*-price (see appendix A for more information). We chose to model the decision-problem faced by the seller as a Markov Decision Process (MDP). In this MDP, depending on the state of the seller, which includes competition parameters and cash position, the seller has to choose an action – *SLA* price – such that future rewards are maximized. Seller’s decision problem is written in the following manner:

$$\Phi^P (State, P_i) = \sum_{State'} \mathfrak{S}_{State \rightarrow State'}^{P_i} \left[ \mathfrak{R}_{State \rightarrow State'}^{P_i} + \max_{P_i'} \Phi^P (State', P_i') \right]$$

$$V^P (State) = \max_{P_i} \Phi^P (State, P_i)$$

where the environment controls the following parameters:  $\mathfrak{R}_{State \rightarrow State'}^{P_i}$  is the reward generated (profit or loss) as the state transitions from *State* to *State'* with probability  $\mathfrak{S}_{State \rightarrow State'}$ . The reward changes the cash position, one of the parameters of the state of the seller and can be associated with the terms defined earlier:

$$\mathfrak{R}_{State \rightarrow State'}^{P_i} = \begin{cases} P_i - MC_{time} * t_i - P_b & \text{if seller - agent wins} \\ -MC_{time} * t_i - P_b & \text{if seller - agent loses} \end{cases}$$

If the values of the transition probabilities and the rewards are known, the solution to this MDP can be attempted directly. However, these values are not known and are estimated only by exploring. The MDP can be solved using different techniques including Reinforcement-Learning techniques (Sutton and Barto 1999) such as Q-learning and Sarsa-Learning techniques. The key difference between the two techniques is that, Q-learning converges slowly since it has to gather information about each action under each

state over numerous executions, while Sarsa-learning technique combines the learning with decision-making (Sutton and Barto 1999). Our choice of technique is based on this criterion and therefore, we choose to adopt the Sarsa-Learning technique.

For the sake of finiteness of the set of possible *SLA* prices, the permissible *SLA* price values are limited to integers, multiples of ten in the range  $[0, Q]$ . In the following subsections we discuss strategies adopted in each information environment (See appendix for implementation details).

### 5.2.1 Zero-Information Environment

To a seller-agent, the environment is a black box that only provides information if its *SLA* was successful; and therefore, the knowledge is limited to being local. Seller-agents speculate about the presence or absence of rivals based on the outcomes of *SLAs* submitted. A seller-agent may win, either because the *SLA* it submitted was the best among the competing *SLAs*, or when it is the only seller-agent in the marketplace. In Sarsa-Learning, after a profit (loss), the tendency, represented by  $\Phi^P(\text{State}, P_i)$ , that generates the chosen action,  $P_i$ , is reinforced (weakened). In the modified algorithm, after every successful market session, the  $\Phi^P(\text{State}, P_i)$  values for all price-values (actions) below the quoted-price (chosen action) are reinforced. Similarly, after an unsuccessful market session, the  $\Phi^P(\text{State}, P_i)$  values for all price-values (actions) above the quoted-price (chosen action) are weakened. So, we observe the following: after

winning, the seller-agent slowly increases its *SLA* price promising lesser consumer surplus in future market-sessions. If no other seller-agent is present in the marketplace, the seller-agent eventually increases its *SLA* price to monopoly price ( $P_i = Q_i^p$ ) extracting the consumer surplus completely. However, while increasing the *SLA* price, if the seller-agent loses even after promising a positive consumer surplus, then it indirectly learns about the presence of at least one other seller-agent. The losing seller-agent is not aware of the consumer surplus promised by the winning seller-agent and so it explores in future market sessions, by lowering its *SLA* price and improving its chance of winning. This process of increasing and decreasing prices continues across the different market sessions. The range of allowable prices dictates the stopping condition.

### **5.2.2 Quasi-Information Environment**

In this information environment, the broker disseminates only the information about the winning *SLA*. Seller-agents in addition to having private knowledge about their outcomes also acquire common knowledge – price and quality promised as a part of the winning *SLA* (the delivered quality is not made public). Note that the common knowledge is also part of the private knowledge held by the winning seller-agent. To the winning seller-agent, the quasi-information setting does not add any more information than it possesses and it observes an environment similar to the Zero-Information Setting. Its response is also similar to that of the winning agent in the Zero-Information Setting. Meanwhile losing seller-agents use the common knowledge to compare their *SLAs*

against the winning *SLA*. The Sarsa-learning technique is modified such that the  $\Phi^P (State, P_i)$  values for all possible price-values (actions) above the best response *SLA*-price (action chosen by the opponent) are weakened and so, we observe that the response of a losing seller-agent is dependent on its model-building dominance<sup>8</sup>. If the losing seller-agent,  $i$ , agent realizes its model-building dominance over the winning seller-agent,  $j$ , the dominant strategy for seller-agent  $i$  in future market sessions is to quote an *SLA*-price equal to utility generated by seller-agent  $j$ ,  $P_i = Q_j^P$ . If the losing seller-agent,  $i$ , is not dominant in its machine building ability, then for future market sessions, it initiates a price war. If it undercuts the surplus promised by the winning seller-agent by  $d$ , the *SLA* price for future market sessions is  $P_i = Q_i^P - (Q_j^P - P_j) - d$ .

### 5.2.3 Complete-Information Setting

In the complete-information setting, the common knowledge disseminated is the *SLA* submitted by all participating seller-agents. Ex-ante, information about the qualities of other seller-agents is not available. However ex-post, each seller-agent knows a) the number of seller-agents that participated in the previous market session b) its *SLA* in comparison to other seller-agents in the marketplace. The dominant strategy equilibrium is for the seller-agent that is dominant in terms of its machine building ability to submit

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<sup>8</sup> If the expected quality,  $Q_i^P$ , of seller-agent  $i$  is higher than  $Q_j^P$ , the expected quality of seller-agent  $j$ , then seller-agent  $i$  is dominant

an *SLA*-price  $P_i = Q_j^P$ , where  $Q_j^P$  is the quality of the second-dominant seller-agent in the marketplace. Other seller-agents initiate a price war well aware of the dominant seller-agent. Note that the promised quality information disseminated, is not guaranteed to be perfect since they may be based on the regression coefficients that may not have converged.

## 6. Results

We analyze and compare social welfare, consumer surplus and the producer surplus generated in each setting. For this, we executed market sessions with two seller-agents in the marketplace. Limiting the number of participating sellers helps us to understand the effects of different parameters in a simplified setting. The two seller-agents in our marketplace have different predictive-model building capabilities. One uses Naïve-Bayes method and the other uses random method. Random-agent incurs low model-building cost but the quality delivered is low. However, the Naïve-Bayes agent incurs high model-building cost but delivers high quality. Although the seller-agents specialize in different machine-learning methods for building predictive models, they adopt the same learning technique explained in sections 5.1 and 5.2. After making enquiries at the Pittsburgh Super Computing Center, we chose a value of 40\$/hr (0.00001\$/ms) for the marginal cost of computing. The *SLA*-processing fee was set to  $P_b = \$0$ . The value for initial endowment was set to  $M = \$800$ . We executed 1000 market sessions with each

information environment and compared the results.

## 6.1 Performance Analysis

Table 2 shows the differences in average consumer surplus and average producer surplus for the 1000 market sessions. Differences are calculated only between settings that have incremental information revealed – Complete-Information Setting versus Quasi-Information Setting and Quasi-Information Setting versus Zero-Information Setting. The last row in the table shows the difference in the social welfare generated between the Zero-Information Setting and the Complete-Information Setting. Values in parenthesis indicate the standard deviation of the mean.

	Complete-Information & Quasi-Information	Quasi-Information & Zero-Information
Difference in Consumer Surplus	6.52 (0.74)**	6.53 (0.76)**
Difference in Producer Surplus	-8.74 (0.88)**	-4.17 (0.88)**
Social welfare between Complete and Zero-Information Settings	0.19 (0.96)	
Social welfare between Complete and Zero-Information Settings at $P_b = \$10$	-0.16 (0.85)	

Table 2: Comparative Statistics (\*\*: indicates significance at the 95% level)

One can see that the Complete-Information Setting generated higher consumer surplus (statistically significant at the 95% level) than both the Zero-Information Setting and the Quasi-Information Setting. In fact, consumer surplus increases monotonically with information revealed (the differences are statistically significant at the 95% level). This is against our expectation (against hypothesis 1). Similarly, the producer surplus

decreases monotonically with information and the differences were significant at 95% level. These were also against our expectation (against hypothesis 2). We analyze and attribute this to the learning in the marketplace. Unlike the static model, the seller does not know the probability of its opponent participating or the quality delivered by its opponent. Sellers have to learn about their marketplace in the Zero-Information Setting. The only mechanism by which sellers checked if competition exists is by lowering the consumer surplus and using the outcome to gain information about competition. This may be the reason why the producer surplus lowers with the information revealed in the setting. Our computational marketplace results although are different from the static analytical models discussed earlier, conform to the results produced by Thomas (1996).

In our hypothesis 3, we expected the social welfare generated in the Complete-Information setting to be lower than that in the Zero-Information Setting. We find that the difference in social welfare generated between the two settings is not significant. At an *SLA*-Processing fee of  $P_b = \$0$ , the cost of participation is low. At low participation cost, sellers the aggressiveness of competition is similar in both settings with the high-quality agent winning same number of market sessions in both settings. In the following paragraph, we specifically analyze the effect of *SLA*-processing fee by setting  $P_b = \$10$ . This is done in addition to analyzing the sensitivity of our results to *SLA*-processing fee in section 6.2.2.

In all three settings, with  $P_b = 10$ , the random agent gets evicted from the marketplace.

Figure 5 shows the average of the consumer surplus for the previous 100 market sessions under each setting. Circular points in the figure indicate the market sessions when the random agent gets evicted. Subsequent market sessions have only the Naïve-Bayes agent participating. The following paragraph provides intuition into why the random-agent survives longer in some settings and is evicted sooner in others.

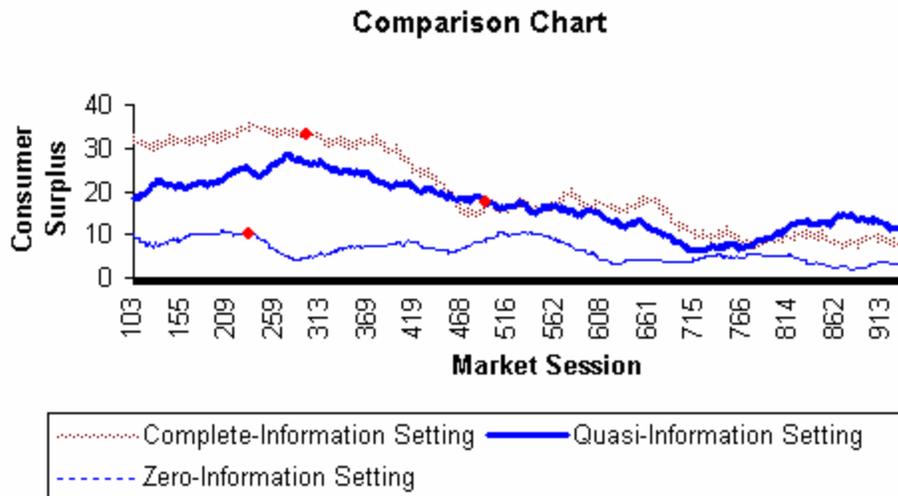


Figure 5: Average Consumer Surplus in all three settings

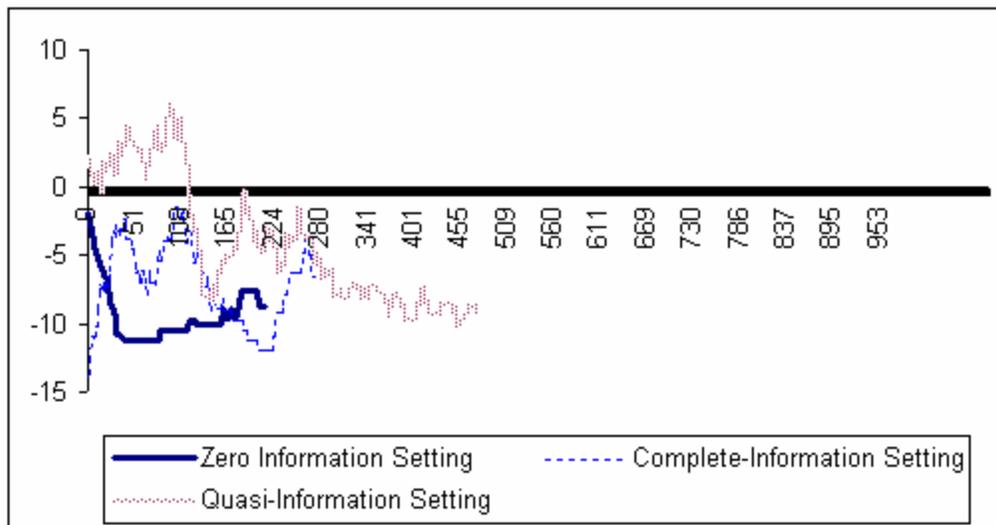


Figure 6: Average loss incurred by the random-agent

Sellers explore to learn both their model-building abilities and competition. Exploration, with an SLA-processing fee, increases (decreases) the rate at which the cash-position depletes (increases). Figure 6 shows the average loss incurred by the random agent in all three settings. In the Zero-Information Setting, after the initial exploration, the random-Agent does not have the quality dominance to compensate for the exploration and therefore is evicted. The Complete-Information Setting provides information about competition and eliminates the need for exploring. The random-agent, although initiates a price war, is able to survive longer with its cash-position that was not exhausted exploring. In the Quasi-Information Setting, the random-agent benefits from the asymmetric nature of the information revealed. The random-agent wins market sessions when the high-quality agent explores. Revenue generated in those wins is greater than that generated during the price wars of the Complete-Information Setting. Note that we compare only the revenue per win and not the number of wins. With this increased cash-position, the low-quality agent survives longer in the Quasi-Information Setting than in the Complete-Information Setting. After the random agent is evicted from the marketplace, the average consumer surplus curve falls. This conforms to the result from our analytical model – as long as the sellers are in duopoly the consumer surplus promised rises. Right after the random agent gets evicted from the marketplace, the Naïve-Bayes agent charges monopoly profits promising lower consumer surplus.

We compare the social welfare difference between the Complete-Information Setting and the Zero-Information Setting again but find that this difference is also not significant.

This can be attributed to the information provided by the Complete-Information Setting, which eliminates the need for exploring and facilitates the survival of the low-quality agent. Because of this, the low-quality agent wins more frequently. When a low-quality agent wins a market-session, the social welfare for that market-session is lower than when the high-quality agent wins. Since the random agent survives longer in the Complete-Information Setting and the average social welfare is calculated over all the 1000 market sessions, the average social welfare decreases.

## 6.2 Sensitivity Analysis

One would expect producer profits to decrease with increase in either the marginal cost or the *SLA*-processing fee. However, their impact on the welfare generated is unclear. So, we analyze the sensitivity of our results presented in the earlier section, first, with respect to marginal cost of computing and, second, with respect to *SLA*-processing fee.

### 6.2.1 Sensitivity to Marginal Cost

		Complete-Information	Quasi-Information	Zero-Information
MC=0.0000111	Consumer Surplus	24.66 (0.40)	18.16 (0.64)	11.63 (0.43)
	Producer Surplus	33.44 (0.52)	42.16 (0.71)	46.33 (0.72)
	Social welfare	58.13 (0.68)	60.33 (0.69)	57.94 (0.69)
MC=0.0111	Consumer Surplus	24.16 (0.41)	20.74 (0.52)	17.16 (0.57)
	Producer Surplus	33.02 (0.53)	36.6 (0.71)	39.86 (0.67)
	Social Welfare	57.19 (0.51)	57.34 (0.69)	57.03 (0.69)
MC=0.111	Consumer Surplus	19.79 (0.51)	18.77 (0.44)	15.21 (0.61)
	Producer Surplus	13.78 (0.51)	17.03 (0.55)	19.12 (0.62)
	Social Welfare	33.80 (0.73)	35.82 (0.61)	34.39 (0.77)

Table 3: Sensitivity to Marginal Cost

Table 3 shows the average consumer surplus, average producer surplus and social welfare generated under different marginal costs with  $P_b = \$0$ . We find that the producer surplus generated decreases and the consumer surplus increases with increase in information revealed (producer surplus and consumer surplus differences between the Zero-Information Setting and the Quasi-Information Setting, and between the Quasi-Information Setting and the Complete-Information Setting are statistically significant at the 95% level). Our results here are similar to that presented in the earlier section for hypothesis 1 and 2. We also find that the difference in social welfare generated between the Zero-Information Setting and the Quasi-Information Setting is not significant at the 90% level and against our expectation. This is consistent with our earlier result on hypothesis 3.

Another interesting observation is that social welfare generated in the Quasi-Information setting is the highest among the three settings. This is due to the asymmetric nature of information revealed in the Quasi-Information Setting. In the Quasi-Information Setting, losing sellers receive information about the winner's *SLA* while the winner does not receive any additional information. This is different from the symmetric nature of information revealed in other settings. In the Complete-Information Setting, all sellers have complete information about the environment as while in the Zero-Information Setting no seller has any information. Because of this asymmetry, the random agent is not able to initiate a price war as effectively as in the Complete-Information Setting. For every win, the random-agent exposes its model-building capability to the high quality

agent without acquiring any additional information in return. This makes it difficult for the random-agent to bid effectively in subsequent market sessions since it lacks information about its competition. This “ineffective” price war is due to the asymmetric nature of information revealed. Although it gains information about its competitor when the high-quality agent wins, the random-agent is not able to effectively use the information gained since it lacks the model-building dominance. Therefore, we find that the Naïve Bayes agent wins more frequently in the Quasi-Information Setting than in the Complete-Information Setting and therefore, the average social welfare is higher in the Quasi-Information Setting.

### 6.2.2 Sensitivity to the SLA-Processing Fee

		Complete-Information	Quasi-Information	Zero-Information
$P_b = \$0$	Consumer Surplus	24.66 (0.40)	18.16 (50.23)	11.63 (0.43)
	Producer Surplus	33.44 (0.52)	42.16 (0.71)	46.33 (0.72)
	Social welfare	58.13 (0.68)	60.33 (0.69)	57.94 (0.69)
$P_b = \$4$	Consumer Surplus	25.87 (0.62)	22.27 (0.51)	14.72 (0.52)
	Producer Surplus	25.93 (0.66)	30.21 (0.71)	38.07 (0.78)
	Social Welfare	55.80 (0.73)	56.48 (0.71)	56.79 (0.79)
$P_b = \$10$	Consumer Surplus	17.78 (0.71)	14.17 (0.46)	5.61 (0.35)
	Producer Surplus	21.07 (0.73)	20.61 (0.75)	33.84 (0.75)
	Social Welfare	48.85 (0.54)	44.82 (0.71)	49.49 (0.74)

Table 4: Sensitivity to SLA-Processing Fee.

Table 4 shows the social welfare generated when the market sessions were executed for different values of  $P_b$ . Consumer surplus increases monotonically with information revealed – this violates hypothesis 1; the difference in social welfare generated between the Complete-Information Setting and the Zero-Information Setting is not significant –

this violates hypothesis 3. We find that social welfare generated in the Quasi-Information Setting, when the *SLA*-processing fee is \$0 and \$4, is higher than the other two settings and this is consistent with our earlier observation.

But at *SLA*-processing fee  $P_b = 10$ , the social welfare generated in the Quasi-Information Setting is the least among the three settings and this result is striking. Recall that we showed that the low-quality agent survives longer when  $P_b = 10$ . Because of this, the random-agent has higher chance of winning more frequently and this leads to lower social welfare than even the Quasi-Information Setting. We find that producer surplus is non-increasing with increase in information.

## 7. Conclusion

Our work is distinctive in its focus on learning. A closed form solution is applicable only in cases where information about the topography of the marketplace – monopoly or duopoly or multi-agent – is available ex-ante. When such information is unavailable, the sellers have to search and adapt their strategies accordingly. Closed-form analytical solutions cannot be extended to an algorithmic framework and therefore, the need for a computation-based approach. Analytical models developed for the static set-up generated very different results from our computational marketplace. In the presence of competition, sellers were competing to outbid their opponents and thereby, increasing the consumer surplus promised. After evicting all its competitors from the marketplace, the monopolist seller extracts the consumer surplus by submitting monopoly *SLA*. Our

analysis is restricted to duopoly competition but we could not extend it to a multi-seller marketplace because of implementation limitations.

From our computational marketplace, we find that producer surplus decreases while consumer surplus increases with increase in information revealed. Also, the social welfare generated in the Complete-Information setting is not statistically different from that in the Zero-Information Setting. From our observation, we also find that the Quasi-Information Setting generates higher social welfare than the other two settings – Complete Information Setting and the Zero-Information Setting.

To demonstrate the usefulness of our results, we apply them to analyze a specific instance of web services marketplace – reverse-auction marketplace. Remember that most reverse-auction marketplaces such as Freemarkets, Covisint, and VerticalNet operate to support buyer-side procurements, and so, should be seeking to maximize consumer surplus and not the social welfare. Based on our results, the average consumer surplus generated in the Complete-Information Setting is the highest and therefore, reverse-auction marketplaces should be adopting the Complete-Information setting and not the currently popularly implementation which we refer to as the Quasi-Information setting. However, consumer surplus cannot be the only driver in deciding the *information environment*. Other parameters such as producer surplus should also be analyzed. From our results we find that the producer surplus generated is least in the Complete-Information Setting. If the producer surplus generated in the reverse-auction marketplace adopting the Complete-Information Setting is lower than that from other channels (say

a competitive marketplace), according to Milgrom (2000), sellers will move to these alternate channels abandoning the reverse-auction marketplace with Complete-Information Setting. This paper does not compare the competitive marketplace to the reverse-auction marketplace although this can be analyzed using a similar set-up.

In our computational marketplace, we model only the sellers' exit from the marketplace and not the entry of new sellers into the marketplace. In such a case, the incumbent sellers perceiving competition from the entrants could initiate a price war. During the price war, a high quality entrant may still be driven out if the cash position of the low-quality incumbent is high enough to sustain the price war. Typically, sellers tend to serve market-niches and avoid direct price competition. The direct price war, we see in our marketplace, is due to the lack of heterogeneity in the consumer preferences assumed. Consumers in our marketplace participate in all market sessions and choose the seller offering maximum consumer surplus independent of the price quoted in the *SLA*. Niches tend to occur only in cases where consumers are differentiated by their buying power – money they can afford to pay.

In conclusion, we believe that the computational-based approach is a useful means to understand problems that are difficult to be modeled analytically, but are key in designing emerging electronic markets. We propose to continue investigating this line of research to analyze and compare other electronic market designs.

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**Appendix A: Duopoly with Topography Information**

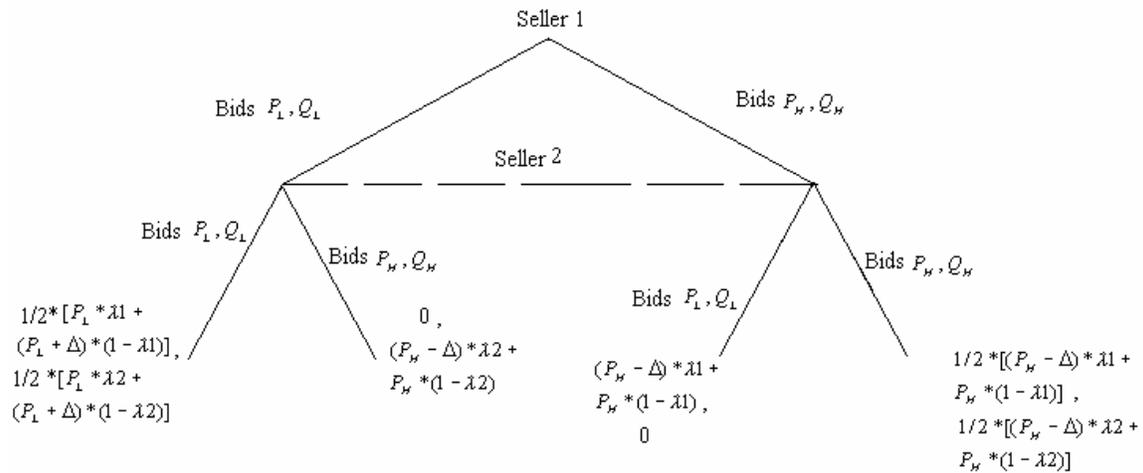


Figure A.1. Sellers know topography as duopoly.

For the sake of clarity we redraw figure 2 as figure a.1. Let seller-1 bid the *SLA* pair  $(P_L, Q_L)$  with a probability of  $\mathbf{a}_1^{w/inf}$  and the pair  $(P_H, Q_H)$  with a probability of

$1 - \mathbf{a}_1^{w/\text{inf}}$ . Then, the expected profit for seller-2 when bidding the SLA-pair  $(P_L, Q_L)$  is:

$$\mathbf{a}_1^{w/\text{inf}} * [1/2 * (P_L + \Delta * (1 - I_2))] + (1 - \mathbf{a}_1^{w/\text{inf}}) * (0) \dots\dots A.1$$

Similarly the expected profit for seller-2 when bidding the SLA-pair  $(P_H, Q_H)$  is

$$\mathbf{a}_1^{w/\text{inf}} * (P_H - \Delta * I_2) + (1 - \mathbf{a}_1^{w/\text{inf}}) * [1/2 * (P_H - \Delta * I_2)] \dots\dots A.2$$

The mixed strategy equilibrium is determined by equating (A.1) and (A.2) and solving

for  $\mathbf{a}_1^{w/\text{inf}}$  we get

$$\mathbf{a}_1^{w/\text{inf}} = \frac{(P_H - \Delta * I_2)}{\Delta - (P_H - P_L)} \dots\dots A.3$$

Symmetrically, for seller-2, the probability with which it chooses the pair  $(P_L, Q_L)$  is

$$\mathbf{a}_2^{w/\text{inf}} = \frac{(P_H - \Delta * I_2)}{\Delta - (P_H - P_L)} \dots\dots A.4$$

The expected profits for seller-2 can be calculated as

$$\begin{aligned} \Pi_{duopoly-1}^{w/\text{inf}} = & \mathbf{a}_1^{w/\text{inf}} * [1/2 * (P_L + \Delta * (1 - I_2))] + (1 - \mathbf{a}_1^{w/\text{inf}}) * (0) + \\ & \mathbf{a}_1^{w/\text{inf}} * (P_H - \Delta * I_2) + (1 - \mathbf{a}_1^{w/\text{inf}}) * [1/2 * (P_H - \Delta * I_2)] \end{aligned}$$

Substituting values for  $\mathbf{a}_1^{w/\text{inf}}$  and  $\mathbf{a}_2^{w/\text{inf}}$ , we get

$$\Pi_{duopoly-1}^{w/inf} = \frac{(P_H - \Delta * I_2) * (P_L + \Delta * (1 - I_2))}{2 * (\Delta - (P_H - P_L))}$$

We also compute the consumer surplus generated in the marketplace.

$$CS_{duopoly}^{w/inf} = a_1^{w/inf} * a_2^{w/inf} * (Q_L - P_L) + [a_1^{w/inf} * (1 - a_2^{w/inf}) + (1 - a_1^{w/inf}) * a_2^{w/inf} + (1 - a_1^{w/inf}) * (1 - a_2^{w/inf})] * (Q_H - P_H)$$

Substituting values for  $a_1^{w/inf}$  and  $a_2^{w/inf}$ , we get  $CS_{duopoly}^{w/inf} =$

$$\frac{(P_L * (Q_H - P_H) - Q_H * P_H + \Delta * (Q_H - P_H - I_1 * (I_2 * Q_H - P_H) + I_2 * (I_1 * Q_L + P_H))}{(\Delta - (P_H - P_L))}$$

## Appendix B: Uncertainty about Topography

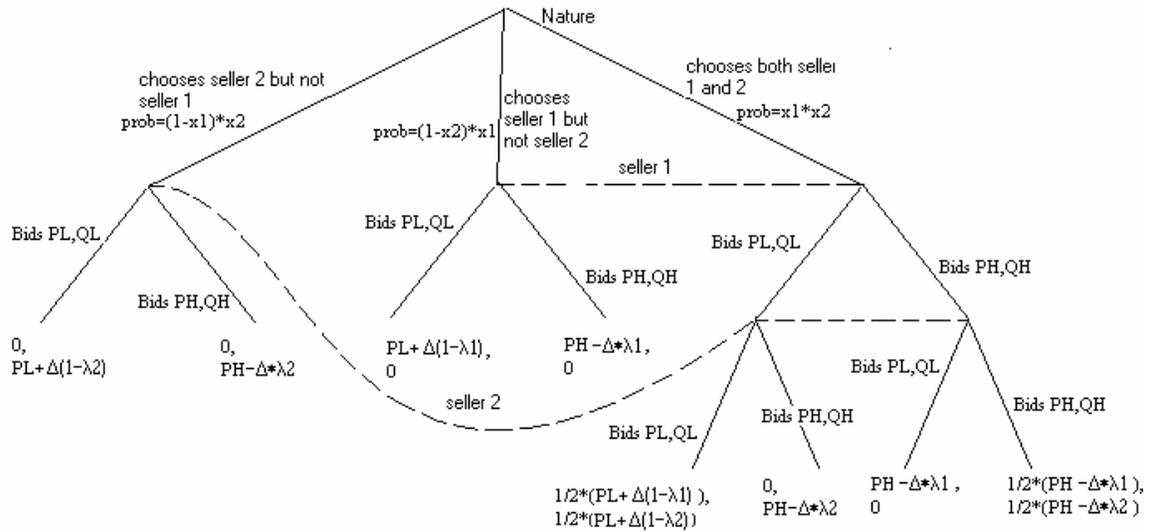


Figure 3 is redrawn in figure b.1 for the sake of clarity. Here we assume that seller-1 bids

the SLA pair  $(P_L, Q_L)$  with a probability of  $a_1^{wo/inf}$  and the pair  $(P_H, Q_H)$  with a

probability of  $1 - \mathbf{a}_1^{wo/inf}$ . Nature determines the participation for each seller with a certain probability. We define  $X_1$  as the probability for seller-1's participation and  $X_2$  for seller-2's participation. Then, the expected profit for seller-2 when bidding the SLA-pair  $(P_L, Q_L)$  is:

$$[\mathbf{a}_1^{wo/inf} * [1/2 * (P_L + \Delta * (1 - I_2)) + (1 - \mathbf{a}_1^{wo/inf}) * (0)] * (X_1) * (X_2) + \left. \begin{aligned} & [(P_L + \Delta * (1 - I_2)) * (1 - X_1) * X_2] \end{aligned} \right\} \dots B.1$$

Similarly the expected profit for seller-2 when bidding the SLA-pair  $(P_H, Q_H)$  is

$$\left. \begin{aligned} & [\mathbf{a}_1^{wo/inf} * (P_H - \Delta * I_2) + (1 - \mathbf{a}_1^{wo/inf}) * [1/2 * (P_H - \Delta * I_2)] ] * (X_1 * X_2) \\ & + [(P_H - \Delta * I_2) * (1 - X_1) * X_2] \end{aligned} \right\} \dots B.2$$

The mixed strategy equilibrium is determined by equating (B.1) and (B.2) and solving for  $\mathbf{a}_1^{wo/inf}$  we get

$$\mathbf{a}_1^{wo/inf} = 2 - \frac{2}{X_1} + \frac{(P_H - \Delta * I_2)}{\Delta - (P_H - P_L)} \dots B.3$$

Symmetrically, for seller-2, the probability with which it chooses the pair  $(P_L, Q_L)$  is

$$\mathbf{a}_2^{wo/inf} = 2 - \frac{2}{X_2} + \frac{(P_H - \Delta * I_1)}{\Delta - (P_H - P_L)} \dots B.4$$

The expected profits for seller-2 can be calculated as

$$\begin{aligned}\Pi_1^{wo/inf} &= \mathbf{a}_1^{wo/inf} * [1/2 * (P_L + \Delta * (1 - I_2))] + (1 - \mathbf{a}_1^{wo/inf}) * (0) + \\ &\quad \mathbf{a}_1^{wo/inf} * (P_H - \Delta * I_2) + (1 - \mathbf{a}_1^{wo/inf}) * [1/2 * (P_H - \Delta * I_2)]\end{aligned}$$

Substituting values for  $\mathbf{a}_1^{wo/inf}$  and  $\mathbf{a}_2^{wo/inf}$ , we get

$$\Pi_1^{wo/inf} = \frac{(P_H - \Delta * I_2) * (P_L + \Delta * (1 - I_2))}{2 * (\Delta - (P_H - P_L))} * X_1 * X_2$$

We also compute the consumer surplus generated in the marketplace.

$$\begin{aligned}CS_{duopoly}^{wo/inf} &= X_1 * X_2 * [\mathbf{a}_1^{wo/inf} * \mathbf{a}_2^{wo/inf} * (Q_L - P_L) + \\ &\quad [\mathbf{a}_1^{wo/inf} * (1 - \mathbf{a}_2^{wo/inf}) + (1 - \mathbf{a}_1^{wo/inf}) * \mathbf{a}_2^{wo/inf} + (1 - \mathbf{a}_1^{wo/inf}) * (1 - \mathbf{a}_2^{wo/inf}) * (Q_H - P_H)] \\ &\quad + [\mathbf{a}_2^{wo/inf} * (Q_L - P_L) + (1 - \mathbf{a}_2^{wo/inf}) * (Q_H - P_H)] * (1 - X_1) * X_2 \\ &\quad + [\mathbf{a}_1^{wo/inf} * (Q_L - P_L) + (1 - \mathbf{a}_1^{wo/inf}) * (Q_H - P_H)] * (1 - X_2) * X_1\end{aligned}$$

Substituting values for  $\mathbf{a}_1^{wo/inf}$  and  $\mathbf{a}_2^{wo/inf}$ , we get

$$\begin{aligned}CS_{duopoly}^{wo/inf} &= ((1 - I_2) * Q_H + I_2 * Q_L) * (1 - X_2) * X_1 + ((1 - I_1) * Q_H + I_1 * Q_L) * (1 - X_1) * X_2 \\ &\quad + \frac{(P_L * (Q_H - P_H) - Q_H * P_H + \Delta * (Q_H - P_H - I_1 * (I_2 * Q_H - P_H) + I_2 * (I_1 * Q_L + P_H)))}{(\Delta - (P_H - P_L))}\end{aligned}$$

## Appendix C: Sarsa-Learning Framework

The framework involves defining a) action space b) reward function and c) state space.

The state-space is different for each information environment and is detailed in the following paragraphs. Further details about the implementation of this technique can be obtained from Sutton and Burto (1999).

## C.1 Reward Function

Reward function defines the function that Sarsa-learning technique attempts to learn. We will use the expected winning prize as the reward function. Expected winning prize is the product of probability of winning when bidding a price is  $P$  and the price  $P$  i.e.,

$$E(P) = \text{probWin}(\text{Price} = P) * P$$

## C.2 Action Space

Action space defines the set of possible actions that a learning agent can choose from. In our framework, action space will be set of possible prices. The ‘price space’ will be the set of single-digit decimal values between 0 and 1 i.e., {0.0, 0.1, 0.2... 0.9}.

An *SLA*-price value that offers maximum expected winning price is chosen as the price to market session. Recall that a seller-agent cannot promise negative consumer surplus. This restricts the *SLA*-price to be less than the utility generated with its expected quality.

### C.2.3 State Space:

State space defines exhaustively the environment for the seller-agents to operate. The state space definition is different for each *information environment*. State space definition for each setting is provided below.

#### C.2.3.1 Zero-Information Setting:

State space includes the following characteristics: a) quality bid and b) money left with

the seller-agent at the time of decision. Note that the transition along the ‘quality bid’ dimension is random across the market sessions. Tile Coding is used for these features. Weight corresponding to the ‘quality bid’ bin and the ‘money left at decision’ bin for each action (price) is the expected reward for that action. Action (price) that generates maximum reward is chosen at the point of decision-making.

#### C.2.3.2 Quasi Information Setting:

State space includes the following characteristics: a) quality bid, b) money left with the seller-agent at the time of decision and c) winning surplus. Similar to the earlier case, using the weight corresponding to the ‘quality bid’ bin, ‘money left at decision’ bin and ‘winning surplus’ bin, the best action can be chosen. But, the winning surplus is not available ex-ante i.e., surplus generated by winning *SLA* is available only at the end of the market session. So, to calculate the reward function for a particular action (price) choice, we take a sum of weights corresponding to ‘quality bid’ bin, ‘money left a decision’ bin across all ‘winning surplus’ bins, each weighted by the number of earlier occurrences. In a sense, the winning surplus cannot be directly considered part of the state-space. In short, we use distribution of earlier occurrences of winning surplus to calculate the reward function.

#### C.2.3.3 Complete Information Setting:

State space includes the following characteristics: a) quality bid, b) money left with the seller-agent at the time of decision and c) ‘surplus promised’ for each competing agent.

Similar to the *Quasi-Information Setting*, the surplus promised by each competing seller-agent is not available *ex-ante* for choosing the best action. So, the reward function is evaluated based on the distribution of earlier occurrences of surplus promised.