The Effectiveness of Escrow Model: An Experimental Framework for Dynamic Online Environments**

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Abstract - This paper investigates the mechanism of online escrow service (OES) in consumer-to-consumer (C2C) auctions on the Internet. We derive a discrete-event driven simulation model for the dynamics of OES adoption in electronic markets, which involves four types of agents: the strategic trader, the moral trader, the OES provider and the law-enforcement agent. By applying the Monte Carlo method in computer-based simulations, we demonstrate that the OES business model can effectively block fraud attempts and promote security in online C2C auction markets. However, we find that the prevailing OES fee rates are not set at the profit maximization level. Meanwhile, the simulation results show that the legal mechanisms in electronic markets directly impact the profit of escrow services.

Key words: online escrow service, online auctions, fraud, perceived risk, discrete-event driven simulation, Monte Carlo approach.

I. Introduction

Online consumer-to-consumer (C2C) auctions have turned virtually every Internet user into a potential auction trader. The fast-growing revenue generated by C2C auction businesses portends a promising future for e-commerce. However, the ongoing risk of Internet fraud has appeared as the key factor causing many users to refrain from trading online [3, 19]. According to the Internet Fraud Watch, operated by the National Consumers’ League, in 2002, ninety percent of the fraud cases reported to the Internet Fraud Watch were online auction related, rising from seventy percent in 2001. The average loss per claim in online auction fraud also rose from $326 in 2000 to $411 in 2001 [11].

The anonymity of cyberspace makes it difficult for online traders to assess the integrity of their trading partners [5]. To some, the risks of online trading outweigh the benefits. Thus, building trust among traders and reducing the risks of online trading are key to promote online sales [3].

Currently, One type of prevailing trusted third parties focuses on promoting consumers’ trust towards their trading partners [2] or the online storefronts [10] before the transaction, such as online feedback system (e.g., [2], [16]) and trust-promoting seals (e.g., [10]). However, consumers can hardly recover any loss, if fraud occurs during the transaction. Another type of trusted third parties is referred to as risk relief service [19], which seeks to reduce traders’ risks [8, 14, 18, 20] and help traders recover their losses after the transaction. Many widely accepted online payment services provide risk relief,
but are still far from perfect. For example, PayPal, the popular online payment system, is distinguished from proprietary payment by virtue of its independence from auction sites but only particularly effective on protecting fraud for sellers.\(^1\) Various types of credit cards offer online fraud protection, but only for buyers (e.g. MasterCard’s zero-liability policy).

Recently, online escrow service (OES) has emerged as an important form of risk relief service in online auction markets. An OES functions in the following way: first, it collects payment for merchandise from a buyer; second, once payment is received, it notifies the seller to ship the merchandise; third, the buyer notifies the OES when the merchandise has been received and has been judged to be satisfactory; lastly, the OES releases the buyer’s payment to the seller. Therefore, OES can provide protection for both buyer and seller in a transaction.

As online fraud becomes increasingly prevalent in online C2C auction markets, an increase in the usage of OES should be expected. However, the current adoption rate has remained low. A survey by the National Fraud Information Center reveals that the OES adoption rate is only about 6%.\(^2\) According to Wolverton [24], the service fees charged by OES may be one of the major factors that prevent consumers from adopting the services.

Do OES providers charge too much? Is OES really effective in protecting online traders from fraud? Is OES a viable business model for online C2C auction markets? This research addresses these questions from a system’s perspective to reveal the effects of OES in online C2C auction markets.

In this research, we conceive a discrete-event driven simulation model for OES adoption, and implement simulation experiments using the Monte Carlo approach [6, 17]. Online traders’ decisions at different stages of a transaction are presented in decision trees. The mechanisms of OES are analyzed using statistical inference based on stochastically generated observations. We find that the current OES business model can effectively block fraud attempts, reduce traders’ losses, and promote more secure online C2C auction markets. However, the prevailing OES fee rates are not optimally set for OES providers. Moreover, the various legal mechanisms in electronic markets exert differentiated effects on the profitability of OES.

The rest of the paper is organized as follows. Section 2 establishes a discrete-event driven simulation model that provides a macro view of escrow services in online C2C auction markets. Then, a micro level decision-making model is established and the criteria for traders’ adoption of OES are

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\(^1\) eBay announced the completion of its acquisition of PayPal in October 2002. Billpoint remained a payment option on eBay through the end of 2002 and PayPal has become the payment option on eBay since early 2003. However, PayPal will still be a third party in electronic markets. For example, over 42,000 websites accept PayPal (http://www.paypal.com/cgi-bin/webscr?cmd=_shop-ext, retrieved on May 20, 2004).

\(^2\) According to National Fraud Information Center, “only six percent of those who have bought items have paid through an online escrow service” and five percent of sellers used escrow service to accept payments (http://www.natlconsumersleague.org/onlineauctions/auctionsurvey2001.htm, retrieved on August 20, 2003).
Section 3 presents the implementation issues in the simulation system, including parameter calibration, random number generation, and model validation. Section 4 reports the findings from the simulation experiments. Conclusions and future research are presented in Section 5.

II. Modeling the Escrow Services in Online C2C Auctions

A. Agents and Online Trading Stages

Four agents are defined in online C2C auction markets – the OES provider, the law-enforcement agent and two types of rational and risk neutral traders: the moral type and the strategic type. Moral traders are virtuous and will never cheat under any circumstances. On the contrary, strategic traders may commit fraud in order to reap more benefits. However, a strategic trader may either act honestly or cheat in a transaction depending on which strategy best suits his interests. An OES provider is a trusted third party who provides escrow services to protect online traders from fraud. The law-enforcement agent is part of the legal mechanism to patrol online transactions with reactive enforcement and punish fraudulent behavior.

The interactions among these agents occur within four phases of the trading process: bidding phase, trading strategy decision phase, OES adoption phase, and trade execution phase (Figure 1). The bidding phase is the initial contracting stage when two traders reach an agreement. In the trading strategy decision phase, traders choose an honest strategy or an opportunistic strategy. Moral traders have just one strategy to play - the honest strategy. Strategic traders evaluate the benefits of two different trading strategies, and decide whether to adopt an honest strategy or an opportunistic strategy. During the OES adoption phase, a trader who adopts an honest strategy determines whether to adopt an OES, based on his estimated risk for the occurrence of fraud, and a trader who chooses an opportunistic strategy will not adopt an OES himself. During the trade execution phase, a trader who adopts an honest strategy acts honestly, whereas a trader who adopts an opportunistic strategy may act honestly, cheat, or quit from the trade. Therefore, an honest strategy contains two actions: adopt OES & act honestly, and do not adopt OES & act honestly. An opportunistic strategy contains three actions: do not adopt OES & act honestly, do not adopt OES & cheat, and do not adopt OES & quit the trade. After the trade execution phase, the final results are revealed from the interactions among the four agents.
B. A Causality Model for Online C2C Auction Markets with Escrow Services

A causality model for an online C2C auction market is illustrated in Figure 2. Four agents, named Strategic Trader, Moral Trader, OES Provider, and Law-enforcement Agent, are associated with five exogenous inputs: Exogenous Fraud Rate, Transaction Activities, OES Fee Rate, Law-enforcement Effort, and Penalty Rate. Among these five inputs, Transaction Activities is the one fueling the system, while the other four inputs are dependencies that jointly affect the status of the model. It should be noted that this model is aimed at the global behavior of online C2C auction markets with escrow services at the macro level, not at the micro level of traders’ behaviors.
Figure 2: A Causality Model for OES Adoption in the C2C Auction Market

The main variables in Figure 2 are:

- **Exogenous Fraud Rate.** The percentage of all transactions that have exogenous fraud. Exogenous fraud refers to the potential fraud that may be conducted by strategic traders who have not decided what strategy to adopt before the transaction strategy decision phase (Figure 1).

- **Intended Fraud Rate.** The percentage of all transactions that have the intended acts of fraud. Intended fraud refers to the potential fraud that may be conducted by strategic traders who have decided to adopt opportunistic strategy in the transaction strategy decision phase (Figure 1).

- **Committed Fraud Rate.** The percentage of all transactions that have committed acts of fraud. The committed fraud refers to the fraud actually conducted by strategic traders in the OES adoption & trade execution phase (Figure 1). **Committed Fraud Rate** is usually observable in the market and is commonly regarded as the *fraud rate*.

- **Fraud Discovery Rate.** The percentage of all transactions that have acts of fraud discovered by law-enforcement mechanisms.

- **OES Adoption Rate.** The percentage of all transactions that adopt an OES.
• **Perceived Risk Rate (PRR).** A trader’s subjective estimation of the probability that fraud may occur in a particular trade.

• **Fraud Failure Rate (FFR).** A strategic trader’s subjective estimation of the probability that his act of fraud will be discovered and punished.

• **Penalty Rate.** The percentage of the penalty cost against the transaction value (amount) in a trade.

• **OES Fee Rate.** The percentage of the escrow service fee against the transaction value in a trade.

In addition, we define the following two subordinate variables, which are not utilized in the simulation, but are helpful for evaluating the performance of the simulation outcome:

• **Defrauding Rate.** The percentage of the number of committed fraud against the total number of exogenous fraud. **Defrauding Rate** is equivalent to the ratio of the **Committed Fraud Rate** to the **Exogenous Fraud Rate**, and indicates the prior effect of the OES on online fraud.

• **Fraud Blocking Rate.** The percentage of all acts of intended fraud that are blocked by the OES. **Fraud Blocking Rate** indicates the posterior effect of the OES on online fraud.

We define a causal relationship from variable $x$ to variable $y$ if $x$ directly affects $y$. When $dy/dx$ is greater than zero, it implies a positive causal relationship from $x$ to $y$, and vice versa. A relationship between two variables is noted as $R_n$, where $n = 0, 1, ..., 18$. A positive sign (+) or a negative sign (−) is embedded to suggest a positive or negative causal relationship between the two variables.

In the model, a trader uses his trading partner’s reputation to determine his perceived risk regarding a specific trade [21]. In recent years, eBay’s reputation scoring system has been well accepted by its traders and has become a major reference guiding the traders’ decisions [16]. With eBay’s Feedback Forum, traders are able to rate their trading partners after each completed transaction. The rating is generally related to a specific auction and is designated as a number. A positive comment from a unique trading partner adds one point to a trader’s reputation score; a negative comment reduces a trader’s score by one point, and a neutral comment has no effect on a trader’s reported score. eBay also provides tabulations of positive, negative, and neutral feedbacks in 12-month, 6-month, and one-month windows. A simplified version of the reputation scoring system is used in our model, wherein we use net reputation scores and denote them simply as reputation scores.

**Reputation Scores** is a general state variable for the reputations of all traders in the auction markets and is presented as a number. If a trader has performed honestly in a trade, his reputation score will be augmented (the effect of relationship $R_{14}$). If a trader has committed a fraud, he will receive a negative comment (the effect of relationship $R_{13}$), and his reputation score will be reduced.
To prevent the reputation damage, the trader may initiate a new account with a reputation score of zero, owing to the low cost of changing his online identity [5, 24]. From the scoring system mechanism, we can predict that strategic traders, who may trade dishonestly in some transactions, will possess lower reputation scores than that of moral traders on average.

In deciding whether paying for escrow services will be more beneficial than taking on the risk of fraud, a trader who adopts an honest strategy utilizes his trading partner’s reputation score to adjust his $PRR$ [1]. With the rationality assumption of traders, the propensity of the reputation scoring process will have a twofold effect: the higher the reputation score, the higher the value of the trader’s pseudonym [5], and the lower possibility that the trader will cheat. Therefore, $PRR$ is negatively correlated to the reputation score (the effect of relationship $R_{13}$).

Causal links between state variables in the diagram are the building blocks for the circularity of cause and effect, where the C2C online market system produces the actions that change states. The model captures the dynamics of a C2C online market with two causality loops formed by the causal links. The first loop (L1) is the causality chain for the strategic trader’s expected utility maximization, based on the consideration of potential punishment for dishonest behavior. It shows how strategic traders’ decisions in their trading strategies are influenced by Fraud Failure Rate and Penalty Rate. It indicates that once a strategic trader chooses the opportunistic strategy, his intentions to commit fraud lead to the acts of fraud, which in turn cause his trading partners’ losses. Higher losses reflected from electronic markets might yield policy intervention, resulting in higher Fraud Discovery Rate due to more Law-enforcement Effort and tougher punishments (Penalty Rate). Finally, the higher discovery rate of fraud and the higher penalty rate may deter a strategic trader’s attempts at committing fraud.

The second loop (L2) is the causality chain for traders who adopt honest strategy to maximize their expected utilities by using an OES to protect their online transactions. This loop also affects the expected utility of those traders who adopt the opportunistic strategy, due to the OES involvement. Only traders using the honest strategy make their decisions in this loop at the OES adoption point. This loop demonstrates that fraud causes losses. The higher the losses from the auction market, the higher a trader’s perceived risk, which will stimulate the trader’s OES adoption, and in turn reduce the incentive for strategic traders to cheat, thus lower the overall committed fraud.

Theoretically, there is a feedback from OES Adoption Rate to OES Fee Rate. For example, the fee rate may change according to the service demand. It is not explicitly considered in the model due to the fact that once the service price is determined it will not be dynamically adjusted in accordance with the change of demand, OES Adoption Rate. In order to mend this shortcoming, the effect of OES Fee Rate on OES Adoption Rate as well as other subsequent state variables, such as
Committed Fraud Rate and Trader Losses, is examined in the simulation to reveal the principle for optimum OES pricing.

In the two follow-up subsections we discuss how traders make decisions, and under what condition a strategic trader chooses the honest strategy. We find that PRR plays an important role in influencing traders’ decision-making process for OES adoption and in affecting strategic traders’ strategy decisions. Table 1 lists the notations used in the traders’ decision-making models.

Table 1: Notations

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U_1^c )</td>
<td>The expected utility for the trader using the opportunistic strategy if an OES is not used by his trading partner</td>
</tr>
<tr>
<td>( U_2^c )</td>
<td>The expected utility for the trader using the opportunistic strategy if an OES is used by his trading partner</td>
</tr>
<tr>
<td>( U_1^h )</td>
<td>The expected utility for the trader using the honest strategy if he does not adopt an OES</td>
</tr>
<tr>
<td>( U_2^h )</td>
<td>The expected utility for the trader using the honest strategy if he adopts an OES</td>
</tr>
<tr>
<td>( r )</td>
<td>OES Fee Rate, based on the percentage of the transaction amount</td>
</tr>
<tr>
<td>( p )</td>
<td>Perceived Risk Rate (PRR), ( 0 &lt; p &lt; 1 ), a homogeneously distributed variable to all traders</td>
</tr>
<tr>
<td>( q )</td>
<td>After a trader adopting an OES, his estimated probability that his trading partner may quit from a trade, ( 0 &lt; q &lt; 1 )</td>
</tr>
<tr>
<td>( a )</td>
<td>OES Adoption Rate, where ( 0 &lt; a &lt; 1 )</td>
</tr>
<tr>
<td>( b )</td>
<td>Penalty Rate when fraud is discovered</td>
</tr>
<tr>
<td>( c )</td>
<td>The marginal cost of the escrow service, based on the percentage of the transaction amount</td>
</tr>
<tr>
<td>( f )</td>
<td>Fraud Failure Rate, where ( 0 &lt; f &lt; 1 )</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>The cost of reputation damage if a trader cheats, excluding any legal punishment</td>
</tr>
<tr>
<td>( M )</td>
<td>The transaction amount of the underlying merchandise, also called the settlement price</td>
</tr>
<tr>
<td>( V^b )</td>
<td>The buyer’s net utility value of the merchandise to be purchased after excluding other costs, such as shipping and handling</td>
</tr>
<tr>
<td>( V^s )</td>
<td>Seller’s reservation value of the merchandise, excluding the shipping fee and other costs</td>
</tr>
</tbody>
</table>

C. Trader’s OES Adoption Criteria

A trader who adopts the honest strategy faces an OES adoption decision-making problem. Both moral and strategic types of traders can adopt the honest strategy. We assume that,

1) The OES adoption decision is made according to the following rules: A buyer first decides whether to use an OES and to pay the OES fee; If the buyer adopts and pays for the OES,
the seller does not need to make the OES adoption decision, and does not need to pay the fee; Otherwise, the seller decides whether to adopt an OES by himself and pay the fee.\footnote{The case that two traders jointly pay the OES fee is excluded, because it does not change the market dynamics, but does significantly increase the mathematical complexity.}

2) If fraud occurs, the loss is irrecoverable, regardless of whether the strategic trader is discovered, or whether the loss is recovered later. The possible recoveries from losses could be neglected from a trader’s payoffs.\footnote{According to Thaler et al. \cite{22}, consumers tend to have a myopic attitude toward risk. They would emphasize current risk and normally not consider future recovery because it is uncertain.}

3) No substitution effect is considered regarding other risk relief services, such as insurance.

The decision tree for a trader who adopts the honest strategy is shown in Figure 3 with the payoffs listed in Table 2. After the bidding and trading strategy decision phases, a trader decides to adopt the honest strategy. Then the trader needs to make one more decision, which is whether to adopt OES. If the trader decides not to adopt OES, he is on the upper branch of Figure 3. At the “uncertain point”, he may encounter a trader adopting the opportunistic strategy with subjective probability $p$, or encounter a trader adopting the honest strategy with subjective probability $1-p$. If his trading partner uses the opportunistic strategy and decides to cheat, the trader’s payoff is $\omega_1$; if his trading partner is a trader with honest strategy, the trader gains payoff $\omega_2$.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{decision_tree.png}
\caption{The Decision Tree For a Trader Using the Honest Strategy}
\end{figure}
Table 2: The payoffs of the trader with the honest strategy under different conditions

<table>
<thead>
<tr>
<th>Payoffs</th>
<th>When the trader is a buyer</th>
<th>When the trader is a seller</th>
<th>Explanations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega_1$</td>
<td>$-M$</td>
<td>$-V^*$</td>
<td>When an OES is not adopted, and the trading partner cheats, the trader suffers a net loss.</td>
</tr>
<tr>
<td>$\omega_2$</td>
<td>$V^* - M$</td>
<td>$M - V^*$</td>
<td>Two traders trade honestly without adopting an OES. This is the best outcome for the trader.</td>
</tr>
<tr>
<td>$\omega_3$</td>
<td>$-rM$</td>
<td>$-rM$</td>
<td>The trader adopts an OES, and his trading partner forfeits the trade. This implies the transaction is not completed normally because of the trading partner’s retraction.</td>
</tr>
<tr>
<td>$\omega_4, \omega_5$</td>
<td>$V^* - M - rM$</td>
<td>$M - V^* - rM$</td>
<td>The trader pays for an OES and the trading partner does not cheat.</td>
</tr>
</tbody>
</table>

The scenario that a trader (using the honest strategy) not initiating an OES meets a trader (using the opportunistic strategy) not cheating is listed as impossible cases in the decision-tree. This is because a strategic trader has already evaluated the expected utility of cheating and the expected utility of being honest when he determines whether or not to adopt the opportunistic strategy. As he has chosen the opportunistic strategy, cheating must be more beneficial than being honest. Therefore, when his trading partner does not adopt an OES, a trader using the opportunistic strategy cheats. Detailed explanations for the payoffs can be found in Table 2.

By applying a standard backward induction technique, we can obtain the criteria for a trader using the honest strategy to decide when to adopt an OES. If his trading partner adopts the escrow service, the trader is in the best position, with no worries about fraud. Otherwise, the trader will face one of the following outcomes:

\[
U_1^h = (1 - p) \omega_2 + p \omega_3, \quad \text{if the trader using the honest strategy does not adopt OES} \quad (1)
\]

\[
U_2^h = \omega_4, \quad \text{if the trader using the honest strategy adopts OES} \quad (2)
\]

In equation (1), the trader calculates the expected payoff under two different scenarios when his trading partner can be of honest or opportunistic strategy. In equation (2), when a trader adopts OES, even if his trading partner adopts the opportunistic strategy, the trader’s optimum strategy under the protection of OES is to act honestly because cheating without being caught is impossible and quitting is also less beneficial. Therefore, the payoff of the trader using the honest strategy adopts OES is $\omega_4$.

When $U_2^h > U_1^h$ holds, the trader adopts OES. Therefore, we obtain the following criteria for OES adoption:
\[ p(V^b / M) > r, \quad \text{if the trader is a buyer} \tag{3a} \]
\[ p > r, \quad \text{if the trader is a seller} \tag{3b} \]

Equations (3a) and (3b) reveal the relationships among OES Adoption Decision, OES Fee Rate, and PRR. That is, a seller using the honest strategy adopts OES if his PRR is greater than OES Fee Rate, and a buyer using the honest strategy adopts OES if his PRR scaled by the ratio of the perceived value and the transaction price is greater than OES Fee Rate. As long as the criteria in (3a) or (3b) are satisfied, traders will consider the adoption of OES. This discussion is consistent with the relationships in loop 2, described in Figure 2.

D. Strategic Trader’s Decision Criteria

A strategic trader’s decision-tree is shown in Figure 4. A strategic trader has two decision points. One is right after the bidding stage, at which point the strategic trader evaluates the expected utility of adopting the opportunistic strategy or the honest strategy. If the expected utility of adopting the honest strategy outweighs that of the opportunistic strategy, the strategic trader’s decision afterwards is the same as that of the moral trader’s, and is shown in Figure 3. Otherwise, he does not consider adopting an OES, but instead decides whether or not to cheat after his trading partner makes an OES adoption decision.

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**Figure 4:** Strategic Trader’s Decision Tree
The outcomes indicated as “not possible” in the decision tree are the dominated actions, and will not be reached under the rationality assumption. Therefore, the payoffs of these outcomes are skipped and Table 3 only lists the payoffs for the remaining five outcomes.

**Table 3:** The payoffs of a trader using the opportunistic strategy under different situations

<table>
<thead>
<tr>
<th>Payoffs</th>
<th>If the trader is a buyer</th>
<th>If the trader is a seller</th>
<th>Explanations</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \pi_1 )</td>
<td>( V^b - \sigma )</td>
<td>( M - \sigma )</td>
<td>No OES adoption by both trader; the trader cheats without being caught by legal mechanisms. This is the best outcome for the trader.</td>
</tr>
<tr>
<td>( \pi_2 )</td>
<td>( -bM - \sigma )</td>
<td>( -bM - \sigma )</td>
<td>No OES adoption by both trader; the trader cheats and is caught by legal mechanisms. This is the most unfavorable outcome for the trader.</td>
</tr>
<tr>
<td>( \pi_3 )</td>
<td>0</td>
<td>0</td>
<td>Both traders cheat. Since they lose nothing they do not report the fraud case.</td>
</tr>
<tr>
<td>( \pi_4 )</td>
<td>( - \sigma )</td>
<td>( - \sigma )</td>
<td>The trading partner adopts OES, and the trader forfeits the trade.</td>
</tr>
<tr>
<td>( \pi_5 )</td>
<td>( V^b - M )</td>
<td>( M - V^s )</td>
<td>The trading partner adopts OES, and the trader does not cheat.</td>
</tr>
</tbody>
</table>

In Figure 4, when a strategic trader decides to use opportunistic strategy, he waits to see whether his trading partner adopts an OES. If his trading partner adopts an OES, he makes the decision of whether to cheat, quit or act honestly as shown in the bottom branch of Figure 4. If he decides to act honestly, he gains payoff \( \pi_5 \); if he decides to quit, he gains \( \pi_4 \), and so forth.

We first examine the decision criteria of a strategic trader who adopts the opportunistic strategy. Then we analyze how a strategic trader who adopts the opportunistic strategy, in accordance with the different expected utilities, decides whether to trade honestly or cheat. The possible outcomes for a strategic trader using the opportunistic strategy are: 1) if he cheats without being caught, he receives the maximum benefits from his fraudulent action; 2) if he cheats and is caught, he is forced to pay a penalty; 3) if he and his trading partner both cheat, he breaks even; and 4) if he acts honestly due to the adoption of OES by his trading partner, he receives the normal trading surplus.

By applying the backward induction technique, we can posit the strategic trader’s optimal strategies. During the last stage, a strategic trader with the opportunistic strategy obtains the following expected utilities under different OES adoption situations:

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5 This result is derived from the payoff from the decision tree, and omitted to simplify the presentation of the model. The derivation can be obtained upon request from the authors.
When OES is adopted by his trading partner

\[ U_1^e = \max \{ \pi_4, \pi_5 \} = \pi_5 = V^b - M \quad \text{if the strategic trader is a buyer,} \quad (4a) \]
\[ U_2^e = \max \{ \pi_4, \pi_5 \} = \pi_5 = M - V^s \quad \text{if the strategic trader is a seller.} \quad (4b) \]

Therefore, the strategic trader using the opportunistic strategy chooses to “play honestly” at this point due to the fact that “play honestly” yields higher payoffs.

When OES is not adopted by the trading partner

Given this condition, the dominated action of not cheating has been eliminated from the payoff comparison, and when no OES is adopted, a strategic trader using the opportunistic strategy cheats.

The expected payoff from cheating is the following:

\[ U_1^c = (1 - p)[(1 - f)\pi_1 + f\pi_2] + p\pi_3 = (1 - p)[V^b - f(V^b + bM) - \sigma], \]
\[ \text{if the strategic trader is a buyer;} \quad (5a) \]
\[ U_2^c = (1 - p)[(1 - f)\pi_1 + f\pi_2] + p\pi_3 = (1 - p)[M - fM(1 + b) - \sigma], \]
\[ \text{if the strategic trader is a seller;} \quad (5b) \]

where \( bM \) is the fine that a strategic trader has to pay if he is caught cheating. Fraud failure rate \( f \) represents the possibility that the cheating is discovered.

Based on the above trader’s utility analysis, we can derive the conditions for a strategic trader to adopt the opportunistic strategy rather than the honest one at the trading strategy decision phase. The expected utility of adopting the opportunistic strategy \( (U^e) \) can be derived from the above utilities: \( U_1^e \) and \( U_2^e \).

\[ U^e = (1 - a) U_1^e + a U_2^e \quad (6) \]

where \( a \) is the expected ongoing OES Adoption Rate.

The expected utility of adopting the honest strategy can be denoted as \( U^h \), and

\[ U^h = \max \{ U_1^h, U_2^h \}, \]

where \( U_1^h \) and \( U_2^h \) represent the expected utilities without or with OES adoption, respectively, which have been derived earlier. Therefore, we obtain the criterion in which a strategic trader chooses the opportunistic strategy:

\[ U^e > \max \{ U_1^h, U_2^h \} \quad (7) \]

If the above criterion fails, the strategic trader conducts transaction like a moral trader because cheating does not bring him a higher utility. Since the higher OES Adoption Rate results in the lower strategic trader’s expected utility, increasing OES Adoption Rate will push more strategic traders to consider honest trading strategy. The reduced fraud attempts will result in a lower fraud rate and hence a lower PRR. This finally leads to a higher expected utility for moral traders. The discussion here
regarding qualitative relations among several factors for the strategic trader is consistent with the relationships and Loop 1 in the causality model illustrated in Figure 2.

III. Simulation Experiment Design

A. The Discrete-Event Driven Simulation Method

The online C2C auction market modeled in Figure 2 can be considered as a semi-observable system: some of the system state variables are observable, such as Trader Losses and Reputation Scores; and some are not, such as PRR, and Exogenous Fraud Rate. Therefore, it is impossible to apply the analytical method to directly obtain the exact information on questions of interest in this research; nor is it feasible to simulate the system with mathematical modeling, because the relationships among different variables cannot be expressed explicitly in mathematic forms. As a result, the discrete-event driven simulation is a more appropriate method for this study.

Computer simulations have been extensively used in market research [7]. Recent applications include: Spawn, a distributed computational economy, using Monte Carlo approach to study market dynamics [23]; the analysis of traders’ behavior in traditional English common values auctions using Monte Carlo simulation [12]; and PowerWeb, a simulation environment for evaluating electric power exchange auction markets [25]. However, no study in simulating online C2C markets with the Monte Carlo method has been reported.

Based on the Monte Carlo approach, the online C2C auction simulation system is implemented in Perl on a Linux computer. The simulation system can reproduce the dynamics of C2C auction markets with the effects of online escrow services by repeatedly generating C2C transactions customizable with different combinations of parameters. There are seven main functional modules:

- Merchandise posting
- Bidding
- Contracting
- Risk assessing
- Honest trader’s OES adoption decision-making
- Strategic trader’s fraud decision-making, and
- Transaction auditing.

The realizations of the nineteen causal relationships depicted in Figure 2 are illustrated in Table 4.
### Table 4: The Causal Relationship Implementation in the Simulation System

<table>
<thead>
<tr>
<th>Variables &amp; Decision points</th>
<th>Determinants</th>
<th>Implementation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strategic Trader’s Strategy Decision (Strategic trader’s decision point)</td>
<td>Exogenous Fraud Rate ($R_0$)</td>
<td>The criterion for the opportunistic strategy: $U^o &gt; \max{U_{1h}^o, U_{2h}^o}$</td>
</tr>
<tr>
<td></td>
<td>Fraud Failure Rate ($R_{12}$)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Penalty Rate ($R_{10}$)</td>
<td></td>
</tr>
<tr>
<td>Intended Fraud Rate</td>
<td>Strategy Decision ($R_i$)</td>
<td>The adoption of opportunistic strategy is the source of fraud.</td>
</tr>
<tr>
<td>Committed Fraud Rate</td>
<td>Intended Fraud Rate ($R_0$)</td>
<td>If an OES is adopted, the fraud is blocked; otherwise, the fraud is committed.</td>
</tr>
<tr>
<td></td>
<td>OES Adoption Rate ($R_2$)</td>
<td></td>
</tr>
<tr>
<td>Trader Losses</td>
<td>Committed Fraud Rate ($R_2$)</td>
<td>The number of fraud increases if there is a committed fraud. Committed Fraud Rate is calculated with regard to the total number of transactions.</td>
</tr>
<tr>
<td></td>
<td>Honest trader’s Transaction Activities ($R_8$)</td>
<td></td>
</tr>
<tr>
<td>Perceived Risk Rate</td>
<td>Trader Losses ($R_4$)</td>
<td>A trading partner indexed with a number $n$ from a pool of $N$ traders is randomly chosen with the reputation score calculated in: $-\ln(1 - n / N) / 0.003$. Perceived Risk Rate is normally distributed and negatively correlated to the generated reputation score.</td>
</tr>
<tr>
<td></td>
<td>Reputation Scores ($R_{15}$)</td>
<td></td>
</tr>
<tr>
<td>OES Adoption Decision (Honest trader’s decision point)</td>
<td>Perceived Risk Rate ($R_3$)</td>
<td>The criteria of OES adoption: Honest buyer: $p(V^2 / M) &gt; r$ Honest seller: $p &gt; r$</td>
</tr>
<tr>
<td></td>
<td>OES Fee Rate ($R_{17}$)</td>
<td></td>
</tr>
<tr>
<td>OES Adoption Rate</td>
<td>OES Adoption Decision ($R_6$)</td>
<td>The more the OES adoption, the higher the adoption rate.</td>
</tr>
<tr>
<td>Reputation Scores</td>
<td>Trader Losses ($R_{13}$)</td>
<td>Each fraud resets the trader’s score to zero, and a good transaction adds one credit to the trader’s reputation score.</td>
</tr>
<tr>
<td></td>
<td>Honest Transaction Activities ($R_{14}$)</td>
<td></td>
</tr>
<tr>
<td>Fraud Discovery Rate</td>
<td>Law-enforcement Effort ($R_{19}$)</td>
<td>The more losses caused by Internet fraud, the more fraud are discovered owing to the improved Law-enforcement Effort.</td>
</tr>
<tr>
<td></td>
<td>Trader Losses ($R_9$)</td>
<td></td>
</tr>
<tr>
<td>Fraud Failure Rate</td>
<td>Fraud Discovery Rate ($R_{11}$)</td>
<td>The higher Fraud Discovery Rate, the higher Fraud Failure Rate.</td>
</tr>
<tr>
<td>Honest Transaction Activities</td>
<td>Strategy Decision ($R_{16}$)</td>
<td>The adoption of honest strategy increases Honest Transaction Activities.</td>
</tr>
</tbody>
</table>

### B. The Simulation Procedure

The main difficulty in this research is to determine a way to simulate the many unobservable state variables that are associated with human behavior. The key to success lies in controlling the size of the simulation model in such a way that every component in the simulation can be validated and proven to be effective. Therefore, we adopt the strategy in which a simulation system is developed with progressively expanded functionality and start the simulation experiment at a smaller yet more controllable scale. This succinctness eases the implementation of the system with better performance, less uncertainty, and fewer calibration requirements. More features are added afterwards while conducting verifications of consistency between the enhanced system and the primary system. This
approach ensures consistent validity of the system as it grows from a modest size to a more complex and powerful one.

Based on the above ideas, the experiment was conducted in two stages. In the first stage, we focused on the simulation of the Subsystem of Traders Using the Honest Strategy. Using the calibrated parameters and the *OES Adoption Rate* in C2C auction markets, we set up a benchmark set of experiment parameters (see the appendix). Then the relationships between variables in the subsystem of traders using the honest strategy were tested under four different experiment schemes, which have been defined in the appendix as Scheme A, B, C and D. In the second stage, we expanded the simulation to test the whole model with fixed parameters for the subsystem of traders using the honest strategy. The main issues studied in the simulation experiment were, given a certain number of trades initiated by traders:

1) How *OES Fee Rate* affects *OES Adoption Rate*;
2) How to ascertain the relationship between the unobservable *PRR* and *Committed Fraud Rate* by varying other controllable variables;
3) How *OES Adoption Rate* can be affected by other parameters, such as *OES Fee Rate, Exogenous Fraud Rate*, and *PRR*;
4) How to identify *Exogenous Fraud Rate* by the backward inference from other state variables;
5) How OES adoptions block fraud attempts.

C. Parameter Calibration

As we have defined the relationships among system state variables in Figure 2 and obtained equations (3a) or (3b) and (7) for the decision criteria of the different types of traders, the most critical task for customizing the simulation model is parameter calibration [4]. In general, we applied two approaches to the calibration: 1) utilizing reported findings from other empirical studies to establish qualitative relationships among independent observatory variables; and 2) employing the statistics of the OES adoption in C2C online markets published by certain websites, such as fraud.org and CNET news.

The experiment was designed as a repeated event-driven Monte Carlo simulation process [6]. In each virtual trade, a seller and a group of buyers were generated, each being assigned a reputation score. The winning buyer and the seller were matched, and each was randomly and independently assigned a type, either moral or strategic. Once the transaction price was determined, both traders then made their decisions on either adopting an OES or cheating. In this process, the most important parameter to be calibrated is the stochastic properties of *PRR*.

As a behavioral and emotional indicator, *PRR* has the following characteristics [1, 9]:

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• It is randomly distributed among traders due to different risk attitudes and trading experiences.
• It is affected by the trading partner’s reputation score.

Lin et al. [13] report that reputation scores of traders, sampled randomly from different business categories in eBay, demonstrate an exponential distribution. Specifically, the distribution of online traders’ 6-month positive reputation scores can be approximated in the form of $a \lambda e^{-\lambda x}$, where $\lambda$ is between 0.0028 to 0.0034 from several different data sets with $R^2 > 0.8$, and the coefficient $a$ is the upper boundary of the score. We adopted $\lambda = 0.003$ for both the simulation experiment and the human subject based experiment. Thus, reputation scores in a discrete context were generated with the formula:

$$\text{Reputation score} = - \ln(1 - n / N) / 0.003$$

where $N$ is the number of traders configured for the simulation, and $n$ is a random number generated by a program to be evenly distributed in $\{0, 1, ..., N - 1\}$.

The generated reputation distribution then serves for two dependent variables:

1) **PRR.**

PRR as a dependent variable of reputation scores was set as being positively correlated to reputation scores, which was shaped by a truncated normal distribution in interval $[0, 1]$ with the mean higher than that of fraud rate. This treatment is consistent with the primitive simulation result based on a perceived risk simulation model reported in [9].

2) Trader-type (strategic or moral) distribution.

Trader-type distribution was generated according to a preset *Exogenous Fraud Rate*. Given the rational expectation that traders perceive higher risk when their trading partners’ reputation scores are low, we monitored the simulation parameters, and confirmed that traders with higher reputation scores were less likely to be a strategic trader.

Another random variable generated in any virtual trade is the trader’s value rate, which is the ratio between the trader’s perceived value of the auctioned item and the transaction price. It is generated from a uniform distribution in the range of $[1, 1+\Delta]$, where $0 < \Delta < 1$. $\Delta$ captures the reality of online auctions that a range of trading surplus exists. In the experiment, $\Delta$ is used together with PRR to tune the simulation experiment to match the current observed *OES Adoption Rate* in the market.

### IV. Simulation Results

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6 All experiment outcomes are referred to the benchmark parameter settings. If there is no explicit explanation, these benchmark settings are implied.
A. Simulation Model Validation

The validation process of a simulation model determines how well the simulation model predicts the performance of the real system [15]. It is also a parameter-refining process for the model. We have done the following validations to the simulation model:

• If a parameter can be calibrated with the statistics from the market data, we tune it until it falls into a small range that covers the value of the statistics and any deviations from the value (which is still within the range) will not change the qualitative properties of the outcomes.

• If a parameter cannot be calibrated, we test the simulation model’s sensitivity to its variations from the benchmark parameter. The parameter is chosen from a range in which the outcomes are consistent.

• The overall performance of the simulation model is tuned to match the OES adoption rate (6%) in the market, where the benchmark parameter set is fitted.

One issue is the sensitivity of the simulation outcomes to the deviation of the PRR value that is adjustable to calibration. The ideal result is that the qualitative relationships among major state variables will not be changed with variations of the PRR value within a certain range. Bearing this consideration in mind, the ratio of the adjusted PRR and its calculated value has been tested with different schemes of simulation.

According to the decision-making criteria for traders using the honest strategy, PRR directly affects OES Adoption Rate. Suppose under a benchmark PRR setting, the simulated C2C auction system will reach a steady state. We want to investigate the effects of PRR variations on equilibrium. The data from experiment Scheme C show that given a value of Intended Fraud Rate, the PRR estimation has a positive effect on OES Adoption Rate and Fraud Blocking Rate. In Figure 5a, the benchmark value of OES Adoption Rate is obtained when PRR exactly equals Intended Fraud Rate. This figure shows that when the estimated PRR deviates from Intended Fraud Rate, the according OES Adoption Rate deviates much more from the original benchmark value of OES Adoption Rate. In other words, an over-estimation of PRR results in higher growth ratio of OES adoption. This effectively increases Fraud Blocking Rate with a convex trend as shown in Figure 5b. Further simulation shows that the deviation of PRR estimation from Intended Fraud Rate does not change the direction of causal relationships among other variables.
Figure 5. Effect of PRR Estimation

(a) Sensitivity of OES Adoption Rate to PRR estimation when the estimation deviates from the benchmark value (OES Fee Rate = 2%, Intended Fraud Rate = 0.88%).

(b) Sensitivity of Fraud Blocking Rate to PRR estimation when the estimation deviates from the benchmark value (OES Fee Rate = 2%, Intended Fraud Rate = 0.88%).

Figure 6. Effect of OES on Fraud Blocking

(a) Fraud Blocking Rate is positively correlated to OES Adoption Rate. (Exogenous Fraud Rate = 1%; OES Fee Rate varies from 0.3% to 4%)

(b) Owing to OES adoption, the loss from e-markets is significantly reduced. The Rate of Lost Amount from cheating refers to the ratio of the total losses to the total transaction amount. (Exogenous Fraud Rate = 1%; OES Fee Rate varies from 0.3% to 4%).

B. Findings from the Simulation on the Subsystem of Traders using the Honest Strategy

Finding 1: OES can effectively block fraud attempts, reduce traders’ losses, and promote more secure online C2C auction markets.
By intuition, one would expect that adopting an OES would reduce a trader’s potential loss, and this simulation confirms the expectation. Moreover, the increasing and concave shape of Fraud Blocking Rate curve indicates that Fraud Blocking Rate is higher than OES Adoption Rate, since Fraud Blocking Rate curve is above the line of $f(x) = x$ (Figure 6a). According to the simulation, when OES Adoption Rate is 6%, over 13% of the fraud has been blocked. Consistent with Loop L2 in Figure 2, the adoption of OES significantly reduces traders’ losses (Figure 6b). This is equivalent to that OES decreases strategic traders’ benefits from defrauding other traders.

Finding 2: The optimal OES Fee Rate, suggested by the simulation, is less than 2%. This implies that the prevailing 2-4% OES fee rate in online C2C auction markets is too high.

Six groups of simulations with differentiated values of Exogenous Fraud Rate have been implemented; each simulation has been tested with OES Fee Rate varying from 0.3% to 4% in steps of 0.1%. The OES adoption distribution is attained from the simulation within the range of OES Fee Rate from 0.3% to 4%. Figure 7 shows the logarithmic and polynomial approximations of the OES adoption distribution associated with Exogenous Fraud Rate of 1%.

$$y = -0.2161 \ln(x) - 0.7995$$  \hspace{1cm} R^2 = 0.9827

$$y = 961.51x^2 - 44.86x + 0.5547$$  \hspace{1cm} R^2 = 0.9895

According to Hu et al. [9], the optimal OES Fee Rate can be further derived from the OES adoption distribution $S(r)$ by maximizing $(r - c)S(r)$, where $r$ is the value of OES Fee Rate and $c$ is the percentage of the escrow service cost against the transaction amount. As the specific example in Figure 7 shows, $S(r)$ can be approximated in $961.51x^2 - 44.86x + 0.5547$, or $-0.2161 \ln(x) - 0.7995$. Due to the fact that the polynomial distribution fits the best, we adopt it as the OES adoption distribution $S(r)$ and utilize it to obtain the optimal fee rate $r^*$. 
The simulation reveals that the current OES fee rate in online markets has not been optimized. The optimal fee rate derived from the simulation is lower than the current fee rate. The high OES fee rate may contribute to the current low adoption rate.

A sensitivity test shows that the optimal fee rate is positively related to the marginal cost of escrow services, denoted as a cost rate $c$. If the current fee rate of 2% were the optimum, the marginal cost rate $c$ should have been 1.56% (Table 5), which is 77% of the OES provider’s gross income. In such a high cost rate, an OES provider could have difficulties conducting a profitable business when all costs of doing business are taken into consideration. It is suggested in Table 5 that under the 0.88% Intended Fraud Rate, with a reasonable marginal cost of 0.2% of the transaction amount, the optimal OES Fee Rate should be 1.05% and OES Adoption Rate could rise to about 22%. In this case, a higher OES Adoption Rate would prevail and a higher profit for the OES provider would occur. In addition, traders using the honest strategy benefit more by the higher rate of adoption.

Table 5: The Optimum OES Fee Rate Based on the Polynomial Approximation of OES Adoption Function

<table>
<thead>
<tr>
<th>Intended Fraud Rate</th>
<th>Optimum OES Fee Rate $r^*$ (c is the service cost rate)</th>
<th>OES Adoption Rate $a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$c = 0.1%$</td>
<td>$c = 0.2%$</td>
</tr>
<tr>
<td>0.24%</td>
<td>0.72%</td>
<td>0.78%</td>
</tr>
<tr>
<td>0.40%</td>
<td>0.79%</td>
<td>0.86%</td>
</tr>
<tr>
<td>0.63%</td>
<td>0.91%</td>
<td>0.97%</td>
</tr>
<tr>
<td><strong>0.88%</strong></td>
<td><strong>0.98%</strong></td>
<td><strong>1.05%</strong></td>
</tr>
<tr>
<td>1.15%</td>
<td>1.05%</td>
<td>1.12%</td>
</tr>
<tr>
<td>1.38%</td>
<td>1.16%</td>
<td>1.23%</td>
</tr>
</tbody>
</table>

Figure 8: OES Provider’s Profit Rate (Intended Fraud Rate = 0.88%)
Figure 8 presents polynomial approximations for an OES provider’s profit curves with regard to different levels of *OES Fee Rate* from the simulation under different service cost rates. The y-axis represents the percentage of the total profit from OES provision against the total transaction amount. For example, if the marginal cost rate $c$ is about 0.2%, the OES provider’s profit is maximized when *OES Fee Rate* is about 1.05%.

C. Findings from the Complete System Simulation

Finding 3: *Fraud Failure Rate* and *Penalty Rate* are two important factors to prevent strategic traders from cheating. Given a *Fraud Failure Rate*, there exists a critical level of *Penalty Rate* beyond which fraud can be significantly reduced or even completely prevented.

Figure 9 shows that if *Fraud Failure Rate* is low, *Penalty Rate* must be high enough to have a significant effect. However, if *Fraud Failure Rate* is high, low *Penalty Rate* can still play an effective role. For example, when *Fraud Failure Rate* is 10%, a *Penalty Rate* lower than 450% does not have any effect to block fraud. When *Fraud Failure Rate* is 20%, a *Penalty Rate* around 150% starts to be effective, and a *Penalty Rate* around 400% can significantly reduce fraud (and even completely eliminate fraud). This suggests that to effectively deter fraud attempts, the law enforcement agent should endeavor to increase *Fraud Failure Rate* and/or penalties of cheating (*Penalty Rate*). Since a strategic trader’s *Fraud Failure Rate* is practically unobservable, according to the relationship $R_{11}$ in Figure 2, the law-enforcement agent can improve *Fraud Discovery Rate*, so as to increase *Fraud Failure Rate*.

![Figure 9: Sensitivity of Defrauding Rate to the Changes of Fraud Failure Rate and Penalty Rate](image)

Figure 9: Sensitivity of *Defrauding Rate* to the Changes of *Fraud Failure Rate* and *Penalty Rate*
Finding 4: *If online fraud can be significantly reduced, the OES as a stand-alone business will face a challenge to survive.*

Figure 10 demonstrates that the optimal *OES Fee Rate* is positively correlated to *Intended Fraud Rate*. One remarkable aspect of OES is that while a service fee is usually a percentage of the transaction value, the cost of providing an escrow service is relatively independent of each transaction, thus can be viewed as a constant. When *Intended Fraud Rate* gets lower, the optimal *OES Fee Rate* also gets lower, but the cost of providing the service stays unchanged. Therefore, the profits of OES providers are reduced accordingly. With more law-enforcement effort and higher penalty rate for fraud, a lower fraud rate is expected. Moreover, other risk-relief services (e.g., eBay’s standard guarantees and eBay’s PayPal buyer protection program) and online reputation mechanisms can further reduce *Intended Fraud Rate*. Hence, OES is an effective mechanism to prevent fraud under the current market condition wherein online fraud remains a serious concern for online traders. However, the OES market faces substantial uncertainties and challenges. As electronic markets become safer, and as regulations become more effective, OES may cease to remain profitable.

![Figure 10: The Optimal OES Fee Rate vs. Intended Fraud Rate](image)

V. Conclusions and Future Research

This paper investigates the mechanisms of OES for online C2C auction markets and presents four major findings from our computer-based simulation. Methodologically, there are three highlights:

- A discrete-event driven simulation using the Monte Carlo method is conducted in multiple stages with an increasing scope in order to guarantee the consistency and credibility of the simulation outcomes at each increment.
Main simulation parameters are calibrated with the statistics of eBay transactions and the simulation outcomes are validated using the same type of data.

Statistical inferences based on the observations from the simulation experiment are utilized to study the dynamics of C2C auction markets.

Our research sheds light on the viability of the OES business model. The findings reveal that, currently, OES is effective in blocking fraudulent behavior in online C2C auction markets. In addition, the simulation results provide the following insights into the OES market. First, the current OES fee rate could be too high, which in turn yields a low OES adoption rate that prevents the maximization of OES profits. Second, with the reduction in fraud brought about by successful law enforcement, the OES market may gradually dwindle. Finally, whether the OES business model will remain profitable in the near future, and the duration that it can remain so, are all contingent on the security features of future online markets.

This conclusion may explain why the escrow service industry has gone through so many ups and downs in the past a few years. For instance, i-Escrow merged with Trade Direct in 1999 and acquired Tradenable.com in 2000, achieving an 80% share of the OES market in 2000. However, the company went out of business in 2001. Currently, escrow.com (http://www.escrow.com) is the major player in the market. Clearly, the OES market is still in its infancy and undoubtedly it faces substantial uncertainties and challenges. OES providers may have to provide more value-added services and features in the future; otherwise, this line of business may not survive.

Overall, OES is a unique risk relief service. However, understanding the competition between OES and other risk relief services such as insurance and payment processing services (e.g., PayPal) will further justify whether OES is a viable business model in electronic markets. Therefore, the substitution effect between OES and other online risk-relief services could be a good topic for future research. Future exploration in this direction is expected to provide insight into the development of fraud-free online auction markets.

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References:


Appendix: Experiment Parameter Benchmarking and Experiment Schemes

The parameter set for a benchmark experiment scheme contains the following elements:

- The number of trades in a simulation run: 30,000
- The number of traders: 320
- Exogenous Fraud Rate (calculated at the end of each experiment): 0.88%
- The ratio of \( PRR \) and the actual loss rate: 1
- OES Fee Rate: 2%
- Penalty Rate \( b = 100\% \)
- The cost of reputation damage \( \sigma = 0 \)
- Fraud Failure Rate \( \hat{f} \) is set to equal Committed Fraud Rate

Based on the above benchmark parameters the following experimentation schemes are tested:

- **Scheme A:** Exogenous Fraud Rate is varied from 0.05% to 2% in a step of 0.01% to test the system response to different levels of Exogenous Fraud Rate.
- **Scheme B:** OES Fee Rate is varied from 0.3% to 4% in a step of 0.1% to test the effect of OES fee on system dynamics.
- **Scheme C:** The ratio of the estimated \( PRR \) to Intended Fraud Rate is varied from 0.9% to 1.4% to test the effect of perceived risk estimation on the system dynamics.
- **Scheme D:** Combinations of Fraud Failure Rate and Penalty Rate are varied in this scheme to examine the sensitivity of system to law-enforcement policies. In those combinations, Fraud Failure Rate is varied from 1% to 45%, and Penalty Rate is varied from 100% to 500%.