An Analytical and Empirical Analysis of Phantom Transactions in Internet Auction

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ABSTRACT

Internet auction environments make fraud more attractive to offenders because the chances of detection and punishment are lower than offline environments. Therefore, there are many frauds in Internet auctions. One type of fraud is a phantom transaction that involves collusion between the buyer and seller to illegally charge credit card accounts. They pretend to fulfill the transaction paid by credit card, without actual selling products, and seller receives cash from credit card corporations. Then seller lends the money to the card holders at a high interest, in particular where the holders’ credit rating is so bad that he cannot borrow money elsewhere. In this research, we find the optimal prevention measure, one of ex-ante regulations. In addition, we show how to predict and prevent the phantom transactions in Internet auctions and suggest some policy implications.

1. Introduction

Internet auction fraud is currently the number one act of fraud committed over the Internet. A market research company, eMarketer estimated that auction fraud made up 87% of all online fraud in 2000. In 2001, the Internet Fraud Complaint Center (IFCC) alone received over 4,000 auction fraud complaints from January 2001 through April 2001, with total losses from these complaints exceeding $3.2 million. Internet auction fraud involves non-delivery,
misrepresentation, triangulation, fee stacking, black-market goods, multiple bidding, shill bidding, and phantom transaction. These fraud types have been studied but the last one, *phantom transaction* that we address here at the first time to our best of knowledge. This is unique in the sense that it involves collusion by the buyer and seller to illegally charge credit card accounts. Illegal discounting of a credit card involves sellers colluding with buyers by pretending to fulfill the transaction paid by credit card, without actually selling products or services, and sellers receiving cash from credit card corporations. Then before receiving cash from credit card Corporation, the seller lends the money at a high interest rate to the buyer whose credit rating is so bad that he cannot borrow money using normal cash advance services. In online auctions this is more beneficial and less risky than offline. Because the Auction Corporation, a major online auction company in South Korea, acts like as phantom affiliation agency, it is not necessary for a colluder to establish a phantom affiliation and there is no need for business registration to establish credit card transaction with a credit card issue. In other words, Auction Corporation bills credit card company with its name on behalf of sellers. This high touch policy is designed to cope with the problem of the lack of credit information in the country and to encourage more participation by providing more continent payment of credit cards among participants since individual sellers may not accept credit card payment from the seller.

Phantom transactions have damaged Auction Corp’s image. The rumor that about 25% of gross sales revenue is caused by phantom transactions has depreciated the firm’s future revenue. Thus once Auction Corp’s stock price had fallen severely.

To prevent these problems, Auction Corp introduced a system to verify the real identity of
auction participants. It is a prevention measure that checks each individual information, and if it does not correspond to the real information, that person cannot participate an auction proceedings. However this method brings about a trade off between the number of users and the number of offenses. This means that if Auction Corp introduces more restricted prevention measures, the number of innocent Internet users will decrease as well as the number of offenses.

We will introduce an analytical model for determining optimal prevention measures in section 3. In section 4, we will use an empirical test to reveal the characteristics of phantom transactions that make the ex-post detecting easy. In section 5, we will conclude this paper and discuss implications.

2. Literature Reviews

Wang, Hidvegi, and Whinston (2001) point out the identities of the bidders and of the sellers are often masked behind a “handle” or an identification code, and there may not be any actual disclosure of a person’s real identity. In this context, the authors developed analytical models of the ways that reserve price fees can be used to limit the occurrence of shilling in online auctions.

Shinha and Greenleaf (2000) analytically examined optimal reserves and optimal shilling when measured against bidder aggressiveness. Although their work doesn’t pertain to online auctions per se, the authors position shilling as an important issue because of the growing popularity of online auctions. In this research, we empirically examine a phantom transaction as it occurs, and we propose an analytical model.

Klein and Lefler (1981) developed an analytical model that shows how opportunistic behavior
occurs when the profit from misleading customers is greater than the profit from lost sales due to reputation effects. Central to Klein and Lefler’s (1981) and Shapiro’s (1982) work is the concept of punishment when a seller is caught misrepresenting a product or identity. The anonymous nature of Internet transactions can allow Internet sellers to mask their identities, thus increasing information asymmetry and reducing the chance of detection and punishment. In this research, we will show how a reduced chance of punishment can lead to more opportunistic behavior.

DePaulo and Pfeifer (1986), and Johnson, et. al. (2001), discuss how deception detection has a low rate of feedback. DePaulo, Stone, and Lassiter (1985) showed that receivers tend to accept what is told to them at face value, with little thought of deception, thus making deception detection even more problematic. The Internet further exacerbates the problem of deception detection. Internet sellers can assume many identities (e.g. Bunker, 2001; Clemons, Hahn, and Hitt, 2001), making detection that much more problematic, and thus decreasing the rate of detection to an even lower level. However, Johnson et.al. (2001) describe how deceptive behavior can be detected. In their study, auditors that are continuously successful appear to employ heuristics that detects inconsistencies in light of the deceiver’s goals in possible auctions. We employ this kind of method in the present research, by determining how the effects of an auction containing a phantom transaction will differ than auctions containing no phantom transaction, and then we examine those auctions more carefully in comparison to the other auctions.

Bapna, Goes and Gupta (2001) discuss the fact that lot size, opening bid amount, the
magnitude of closing bids and the specified bid increment all affect the revenue generated by an
Internet multi-item auction. A related paper by the same authors (Bapna, Goes, and Gupta, 2000)
uses online auction data to explore and refute some common assumptions about online auction
behavior found in the economics literature (e.g., Milgrom, 1989). Both of these papers delve into
the types of bidders found on multi-item auctions. We extend their results in this research by
comparing seller behavior to bidder behavior, and by investigating bidder response to seller
behavior.

Becker (1968) has demonstrated the usefulness of “conventional” economic analysis is
coming to grips with what is usually considered to be a noneconomic problem – crime and
punishment. Becker has developed a formal model of the decision to commit offenses which
emphasizes the relationship between crime and punishment and he derives criteria for optimal
levels of expenditure on law enforcement and form of punishment subject to a given legal
framework. Harris (1970) suggested that the legal framework need not be taken as constant but is
itself subject to policy choice. Harris proposed to extend the Becker framework to take account
of this additional area of social choice and compare the implication of this model with the
original, less complete version. Stigler (1970) has also approached the determinants of the supply
of offenses in similar terms.

3. Analytical Model

Our primary purpose of this section is to construct an analytical model for reckoning the
optimal prevention measure, which owes much to Gary Becker’s major article.

We assume that the degree of willingness to reveal oneself (\(\alpha\)) is uniformly distributed. The
3.1. Description of Variables

$U_I$: Utility from using the Internet ($U_I > 0$, same for all people)

$N$: Total number of people

$G_o$: Gain per phantom transaction ($G_o > 0$)

$C_s$: Conviction cost (per phantom transaction)

$\alpha$: Prevention measure via identity. We assume that firm can ask customers reveal their identity to certain degree in order to minimize fraud in the Internet.

$P$: Probability of conviction, which is set as

$$P = P(\overline{\alpha}, C_s) = P_0 C_s \overline{\alpha} \quad (P_\alpha > 0, P_c > 0, P_0 < \frac{1}{C_s \overline{\alpha}})$$

$H$: Social harm by unit phantom transaction

$\alpha$: Willingness to reveal oneself ($0 \leq \alpha \leq 1$, uniformly distributed)

$C_{crime}$: Cost of engaging in a phantom transaction set by

$$C_{crime} = C(P, f) = Pf = P_0 C_s \overline{\alpha}f = m_s \overline{\alpha} \quad (m_s = P_0 C, f)$$

$t$: Disutility of revealing oneself on the Internet, $t = t(\alpha, \overline{\alpha})$

$$t = m(\overline{\alpha} - \alpha) \quad if \quad \alpha \leq \overline{\alpha} \quad (m > 0)$$

$$t = 0 \quad otherwise$$

People may feel uncomfortable due to privacy and possible uninvited transactions such as spam mails and advertisements. Thus if one’s willingness to reveal is lower than the prevention measure level, there exists disutility. The variable $m$ means the one’s sensitivity in terms of the
use of private information and we assume every one has the same sensitivity. Now the firm tries to set the optimal prevention level, $\bar{\alpha}$.

3.2. Model

Peoples weigh two utility functions to choose whether they do normal transaction or do commit a fraud. If both the utility from normal and phantom transaction are negative, people do nothing (do not participate in Electronic commerce).

We assume above that willingness to reveal oneself, $\alpha$, is uniformly distributed. When the level of the prevention measure via identity is settled at $\bar{\alpha}$, some people whose willingness to reveal is lower than $\bar{\alpha}$ get disutility $m(\bar{\alpha} - \alpha)$ when using the Internet. Thus some of them will use Internet when net utility of using the Internet is above zero, but others whose negative net utility of using the Internet will not use it. On the other hand, there are other people whose willingness to reveal is higher than the prevention measure ($\bar{\alpha}$). Disutility does not occur for these people.

3.2.1. Case 1 where privacy is concerned $(0 \leq \alpha \leq \bar{\alpha})$

In case 1, people may have three possible utility functions. One is from a normal transaction, another is from a phantom transaction and the other is from do-nothing.

$$
\begin{align*}
\text{Utility} & \quad U_i - m(\bar{\alpha} - \alpha) \quad \text{normal transactions} \\
G_o - m\bar{\alpha} \quad & \quad \text{phantom transactions} \\
0 \quad & \quad \text{do – nothing}
\end{align*}
$$

3.2.2. Case 2 where online provides secure privacy $(\alpha \leq \bar{\alpha} \leq 1)$

Since the online setting of privacy is beyond customers’ tolerance threshold, people exclude
the third option of doing nothing. Thus,

\[
Utility \quad U_i \quad \text{normal transactions} \quad G_o - m_i \zeta \quad \text{phantom transactions}
\]

3.3. Assumptions

First, we assume \( m_i > G_o \). Otherwise, the benefit from engaging in a phantom transaction is always positive. The second assumption is \( U_i < G_o \). It is reasonable that the utility from a phantom transaction is higher than the utility from engaging in a normal transaction if not caught. Third, \( G_o < H \). It is reasonable that the social harm from each phantom transaction is higher than individual gain from engaging in a phantom transaction. Fourth, \( U_i < m \). This means that the sensitivity for revealing private information is higher than the utility from engaging in a normal transaction. Otherwise, the net utility from engaging in a normal transaction is always positive.

3.4. Analytical Results

We use an incentive compatibility condition for representing opportunistic behavior of people among three options: doing a normal transaction, executing a fraudulent one, or shunning the online.

3.4.1. Case 1 where privacy is concerned (\( 0 \leq \alpha \leq \zeta \))

People don’t use the Internet if the utility function is

\[
\text{Do-nothing} \quad U_i - m(\zeta - \alpha) < 0 \quad \text{and} \quad G_o - m_i \zeta < 0
\]
To meet this condition, the prevention measure and willingness to reveal must exist in
\[ \frac{G_o}{m_c} < \alpha \leq 1 \quad \text{and} \quad 0 \leq \alpha \leq \frac{U_I}{m} \]

People engage in a phantom transaction if the utility function is
\[ \text{Phantom} \quad G_o - m_c\alpha \geq 0 \quad \text{and} \quad G_o - m_c\alpha \geq U_I - m(\alpha - \alpha) \]

To meet this condition, the prevention measure and willingness to reveal must exist in
\[ 0 < \alpha \leq \frac{G_o}{m_c} \quad \text{and} \quad 0 \leq \alpha \leq \frac{G_o - m_c\alpha - U_I}{m} \]

People engage in a normal transaction if the utility function is
\[ \text{Normal} \quad U_I - m(\alpha - \alpha) \geq 0 \quad \text{and} \quad U_I - m(\alpha - \alpha) \geq G_o - m_c\alpha \]

3.4.2. Case 2 where personal information is less concerned \((0 \leq \alpha \leq \bar{\alpha})\)

People engage in a normal transaction if the utility function is
\[ \text{Normal} \quad U_I \geq 0 \quad \text{and} \quad U_I \geq G_o - m_c\alpha \]

The interval of the prevention measure is
\[ \frac{G_o - U_I}{m_c} \leq \bar{\alpha} \leq \frac{G_o}{m_c} \]

People engage in a phantom transaction if the utility function is
\[ \text{Phantom} \quad G_o - m_c\alpha \geq U_I, \quad \text{and} \quad 0 \leq \alpha < \frac{G_o - U_I}{m_c} \]

then, demand is \(\bar{\alpha} < \alpha \leq 1\)

This analytical model is divided into three cases by the interval of the prevention measure.
First, when the prevention measure exists between 0 and \(\frac{G_o - U_I}{m_c}\), all choose phantom
transactions.

\[ \text{when } 0 \leq \alpha < \frac{G_o - U_I}{m_c} \]

\[ D_p = \alpha N + (1 - \alpha) N, \quad SW_1 = N(G_o - m_c\alpha - H - C_i) \]

Second, when the prevention measure exists between \( \frac{G_o}{m_c} \) and 1, some people exhibit do-nothing behavior and some people do normal transactions.

\[ \text{when } \frac{G_o}{m_c} < \alpha \leq 1 \]

\[ D_p = \frac{U_I}{m} N + (1 - \alpha) N \]

\[ SW_2 = \frac{U_I}{m} N \int_{-\alpha \frac{U_I}{m}}^{\alpha} (U_I - m(\alpha - \alpha)) d\alpha + (1 - \alpha)NU_I = \frac{U_I^3}{2m^2} N + (1 - \alpha)NU_I \]

Third, when the prevention measure exists between \( \frac{G_o - U_I}{m_c} \) and \( \frac{G_o}{m_c} \), no one chooses do-nothing behavior. That is, all choose either normal transaction behavior or phantom transactions.
Figure 5. Demand when \[ \frac{G_o - U_l}{m_c} \leq \alpha \leq \frac{G_o}{m_c} \]

\[
D_p = (\bar{\alpha} + \frac{G_o - m_c \bar{\alpha} - U_l}{m})N, \quad D_n = (U_l - \frac{G_o + m_c \bar{\alpha}}{m})N + (1 - \bar{\alpha})N
\]

\[
SW_3 = \left(\frac{U_l - G_o + m_c \bar{\alpha}}{m}\right)N \int_{\bar{\alpha} - \frac{G_o - m_c \bar{\alpha} - U_l}{m}}^{\bar{\alpha}} (U_l - m(\bar{\alpha} - \alpha))d\alpha + (1 - \bar{\alpha})NU_l
\]

\[
+ (\bar{\alpha} + \frac{G_o - m_c \bar{\alpha} - U_l}{m})N(G_o - m_c \bar{\alpha} - H - C_i)
\]

In the first case, social welfare is always negative. In the second case, social welfare is always positive. Thus, the optimal prevention measure doesn’t exist between 0 and \[ \frac{G_o - U_l}{m_c} \]. The optimal prevention measure may exist between \[ \frac{G_o - U_l}{m_c} \] and \[ \frac{G_o}{m_c} \]. The exact value of the optimal prevention measure may be a particular point between \[ \frac{G_o - U_l}{m_c} \] and \[ \frac{G_o}{m_c} \] based on the effect of parameters.

3.4.3. Discussion of Analytical Result

Our analytical model shows that harsh prevention measures may eliminate all possible phantom transactions in online auctions. However, such measures also reduce the willingness to participate in the auction mechanism with normal transactions when participants are concerned
about their privacy. Therefore, social welfare can be reduced with harsh prevention measures. On the other hand, if the prevention measures are low enough, participants have potential incentives to engage in phantom transactions. As phantom transactions cause social harm, the market maker must not remain an unconcerned spectator.

Therefore, the optimal level of prevention must be set to the level that allows some phantom transactions. Therefore, prevention measures cannot effectively solve frauds from phantom transactions. This leads to the need for the effective detection measure. In the next section, we suggest some common characteristics of phantom transactions with empirical studies to provide further detection measures.

4. Empirical Studies

We propose five hypotheses on phantom transaction characteristics and define “questionable bidding” which is likely one kind of phantom transaction. In questionable bidding, there are no or few descriptions and pictures of auction products. A normal auction buyer probably will not choose these auctions. Despite the lack of information, however, the products are frequently sold through questionable bidding, and these products are sold very quickly especially in high price products bidding. It is necessary for us to suspect these questionable auctions are phantom transactions. In this section, we will reveal some characteristics of these questionable bids using data which is collected by data collecting agents called information wrappers.

4.1. Empirical Research Hypotheses
We suggest the following five empirical research hypotheses:

**H1: Phantom transactions are more likely to have shorter running auctions than other transactions.**

Because phantom sellers need funds for people with bad credit, phantom sellers will prefer to receive their money from a credit card corporation as soon as possible.

**H2: Phantom transactions are more likely to have fewer bids.**

In order to discourage colluding bidder to bid and win the auction, a phantom auction contains fewer descriptions such as a detailed description and pictures than ordinary auctions. In addition, they set a very brief bidding duration time, and higher starting bid. All of these lead to a fewer bids.

**H3: A high starting bid is associated with phantom transactions.**

An auction with a high starting bid attracts few bidders. If a phantom auction has a high starting bid, it is not probable for other people to the bid.

**H4: A phantom transaction has a higher winning bid within the same product category.**

Engaging in a phantom transaction, fraudulent traders have an expected punishment cost which is defined as the multiplication of the probability of being detected and amount of fine. As phantom traders engage in more auctions, the probability of being detected increases. Thus there are incentives for phantom traders to reduce the number of auctions in which they engage, but these actions involve high winning bids with risk premium.

**H5: A low seller credit rating is associated with phantom transactions.**

Auction Corporation calculates seller credit ratings as well as those of the buyers. Usually the
credit rating of a seller monotonously increases with the number of successfully ended auctions. To reduce the probability of being detected, phantom traders will change identity frequently. Thus a phantom trader’s credit score is lower than other people.

4.2. Detecting and Defining Phantom transaction

For the purpose of this research, the questionable auction we characterize below is used as the operational definition of phantom transactions in our research. A questionable auction is defined as containing these characteristics:

(1) An auction with inadequate product descriptions and pictures
(2) The same item being sold in a different, concurrent auction with adequate product description
(3) An auction with inadequate product description successfully ended at the buynow price

4.3. A conceptual model for phantom transaction

The hypotheses that we suggest result in the following model and we use the model to predict phantom transactions:

\[ \text{Phantom transaction behavior} = f(\text{winbid}, \text{startbid}, \text{number of bids}, \text{auction length}, \text{sellercredit}) \]

4.4. Data

We collect data at [www.auction.co.kr](http://www.auction.co.kr) using a data collecting agent. The data has one category, laptop computer. All collected data involves items valued over one million Won (Korea
currency unit) and the sale ended with a buynow price and are paid by credit card. We collected auction length, start bid, buynow price, winning bid, number of bids, seller ID, and credit scores. The number of auctions fit our characterization is 340. Fifty observations are questionable bidding and 290 observations are normal bidding.

4.5. Logistic Model

4.5.1. Nonlinearity of Binary Choice

Regression models that evoke discrete responses are known as dichotomous, or dummy, dependent variable regression model. There are the three most commonly used approaches to estimating the dummy dependent variable; the Linear Probability Model (LPM), the logit model and the probit model. Because of the binary nature of the dependent variable (i.e., a bidder enters a questionable bid or a normal bid), however, a linear model is inappropriate. The LPM is the simplest of the three models to use but has several limitations, namely, (1) nonnormality of the error term, (2) heteroscedasticity, and (3) the possibility of the estimated probability lying outside the 0-1 bounds. Even if these problems are resolved, the LPM is logically not a very attractive model. It assumes that the conditional probabilities increase linearly when the values of the explanatory variables increase or decrease indefinitely. Therefore what is needed is a probability model that has the S-shaped feature of the cumulative distribution function (CDF).

4.5.2. Logit versus Probit model

Although the CDF is widely used, in practice the logistic and normal CDFs are chosen, the former giving rise to the logit and latter to the probit model. Both logit and probit models
guarantee that the estimated probabilities lie in the 0-1 ranges and that they are nonlinearly related to the explanatory variables. Of the two, the logit model is slightly less involved because by taking the logarithm of the odds ratio, what appears to be a highly nonlinear model becomes a linear model (in the parameter) that can be estimated within the standard OLS framework. In the probit, one is required to invert the normal CDF, leading to errors of approximations unless one has a readily available computer routine. Thus the logit model is generally used.

4.6. Empirical results

The number of observation is 340. 50 observations involve questionable biddings, and 290 observations involve non-questionable biddings. The results are as follows:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Hypothesis</th>
<th>Coefficient</th>
<th>Standard-error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auction length</td>
<td>H1</td>
<td>-0.3071</td>
<td>0.1014</td>
<td>0.0025</td>
</tr>
<tr>
<td>Number of bids</td>
<td>H2</td>
<td>-0.4536</td>
<td>0.5308</td>
<td>0.3928</td>
</tr>
<tr>
<td>Starting bid</td>
<td>H3</td>
<td>3.405E-7</td>
<td>3.819E-7</td>
<td>0.3725</td>
</tr>
<tr>
<td>Winning bid</td>
<td>H4</td>
<td>8.545E-7</td>
<td>4.786E-7</td>
<td>0.0742</td>
</tr>
<tr>
<td>Seller credit score</td>
<td>H5</td>
<td>-0.0349</td>
<td>0.0175</td>
<td>0.0463</td>
</tr>
</tbody>
</table>

Table 1. Phantom transaction parameter estimates

The auction length, winning bid and seller credit score are significant at 1%, 10% and 5% significant level respectively. Thus, we find evidence to support H1, H4 and H5. However we did not find support for two hypotheses; H2 and H3.

After removing insignificant variables, we re-estimate with significant variables.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Hypothesis</th>
<th>Coefficient</th>
<th>Standard-error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auction length</td>
<td>H1</td>
<td>-0.3497</td>
<td>0.0891</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Winning bid</td>
<td>H4</td>
<td>7.662E-7</td>
<td>1.941E-7</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Seller credit score</td>
<td>H5</td>
<td>-0.0352</td>
<td>0.0169</td>
<td>0.0369</td>
</tr>
</tbody>
</table>

**Table 2. Phantom transaction parameter estimates**

The auction length, winning bid and seller credit score are significant at 1%, 1% and 5% significant level respectively.

This result suggests that there surely exist some common characteristics among phantom transactions. Phantom transactions are more likely to have shorter running auctions, higher winning bid and a lower seller credit score. Therefore, we may develop an efficient (detection) alert system based on these common characteristics without discouraging people to use the Internet auction as in harsh prevention measure.

5. Conclusions

In this research, we examine a phantom transaction in Internet auctions. Through analytical modeling, we show that optimal prevention measures exist in some interval that nevertheless allows some phantom transactions. Within the interval, the optimal prevention measure varies depending on the value of other parameters. This incomplete prevention measure drives the need for simultaneous implementation of detection measures. Through empirical tests, we reveal some characteristics of phantom transactions that can help in the development of efficient detection alert measures. Phantom transactions are more likely to have shorter running auctions than other transactions. Phantom transactions have higher winning bid than other transactions within the
same product category of the study (laptop computer). And a lower seller credit score is associated with phantom transactions. Thus the regulation agency must set the level of prevention measures in order to ensure that people can continue using the Internet. Furthermore, after ensuring that all people can participate in using Internet, the regulation agency may rather monitor the transactions in Internet auctions without risking of intruding privacy of netizens. One possible monitoring method is that the regulation agency may utilize auto-alert systems that can capture questionable characteristics and prevent the questionable transactions from succeeding. This paper also demonstrates the usefulness of agent technology (information wrapper) to collect rich data in ecommerce.

This research has some limitations. First, a more delicate analytical model is necessary. In this paper, the results of analytical model are so complex that we obtain some implications only through numerical tests. Second, we collected the data from auction transactions of only one product category, laptop computers. But we believe that these results probably can be generalized to other auctions and to e-commerce and Internet-based selling in general. Third, we collect data using a data-collecting agent only available on Internet auction sites. If more data is available such as delivery information and past transaction records of sellers, more meaningful implications can be obtained with help from auctioneer sites.
But the contribution of this paper is that there is no research that has analytically and empirically examined phantom transactions in Internet auctions with current data. Not only do we show how to set up prevention measure, but we also show that such behavior can be predicted and prevented.

REFERENCES


