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An incentive mechanism to promote honesty among seller agents in electronic marketplaces

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Abstract With the rapid development of online shopping, usually, sellers and buyers have virtual identities, which are not verified beforehand. As a result, establishing trust between sellers and buyers is much harder than before where sellers and buyers would meet face to face before making any transaction. In this work, we propose a method for the marketplace management under anonymous buyers and sellers which makes the honest behavior the most profiting action for rational sellers. In this method, the market operator adopts an honesty promoting mechanism based on direct reward and punishment in which being honest is the most profitable action. In most online marketplaces, a fee or commission is deducted from every payment before settling the account up with the seller. As such, with the dynamic adjustment of the fee, it is possible to reward or punish the seller. The correctness of this method is proven using mathematical models. The apparatus, processes, and algorithms for the marketplace are elaborated in detail so that market operators can easily apply the method in their existing marketplaces.

Keywords Honesty · Trust · E-marketplaces · Reward and punish

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1 Introduction

An Electronic Marketplace [1–4] is a place in which various sellers sell their products to buyers. It is aimed to easily exchange information, sell and buy products and services and make payments.

Many different definitions for e-marketplace can be found in various articles which some are as follows:

- "Electronic markets, by electronically connecting many different buyers and suppliers through a central database, can reduce the need for buyers and suppliers to contact a large number of alternative partners individually." [5]
- "An electronic marketplace (or electronic market system) is an inter-organizational information system that allows the participating buyers and sellers to exchange information about prices and product offerings." [1]
- "An electronic marketplace is a virtual marketplace where buyers and suppliers meet to exchange information about prices and product and service offerings, to collaborate, and to negotiate and carry out business transactions." [6]

To briefly say the specifications of an e-marketplace we can say that it is:

- An appropriate place for buyers to comfortably choose sellers.
- A place in which buyers and sellers can easily exchange information, products, services, and payments.
- An organized infrastructure in which trade operation is done as safely as possible.

In this paper, we assume a market in which only the following primary entities exist.

- Marketplace owner or operator who is a person or an organization that has established the market and usually makes a profit from business transactions in the market.
- Sellers who take advantages of the electronic platform to supply and sell their products and services.
- Buyers who choose products and sellers on this platform and buy their goods by facilities that e-marketplace provides.
- Products or services which are sold and bought in an e-marketplace.

1.1 E-marketplace challenges

In contrast to traditional markets that sellers and buyers meet face to face before making any transaction and could acknowledge the good before paying for that, in e-marketplaces usually, buyers pay in advance, and he/she can receive the product after a period which is mostly needed for production and transportation. So a dishonest seller knows that he will not send the good, or will send a product different from the product the buyer paid for, but the buyer would not be informed till the product is delivered or the delivery period has elapsed. This issue which is known as Reputation Lag in the trust and reputation literature is of special importance and makes the market systems to try to forecast the seller behavior.

To understand and analyze dishonest behavior and its consequences in e-marketplaces, specific definitions have been made. Most important behaviors which are known as attacks are as follows:

- *Dishonesty or Cheating* this kind of attack occurs when a seller does not send the product to a buyer or send something other than what which has been ordered [7]. It is the most important attack in e-marketplaces. In fact, all other kinds of attacks are the actions done by sellers to enable them for this attack.
- *Re-entry* when an e-marketplace security management system unfolds the violation of a seller and takes measures which will result in the seller's loss, he may create a new ID to secure himself of the previous violation consequences [7]. By doing so, all history of the dishonest behavior of a seller would be erased, and he can have his initial status in the system easily. Moreover, he can repeat this process many times. Therefore he can continuously attack in this way and re-enter with a new ID whenever the system is informed of his cheating.
- *Value imbalance* in some e-marketplace security mechanisms, the value of transactions is not considered (like the eBay case) [7, 8]. It means that both a point in a small transaction and large one are considered of even importance. Thus, fraudulent sellers can show honest behavior in small transactions and obtain the related honesty point. However, they can be dishonest in large and more expensive transactions to maximize their profit of dishonesty.
- *Initial window* in some methods, we can predict a seller's behavior based on the results of the previous transactions [9]. However, when there is not enough record of a seller in the initial window, the prediction will be difficult.
- *Ballot stuffing* In most trust and reputation management systems, gaining positive points in e-marketplaces (i.e., higher reputation) leads to trust from more buyers and a larger volume of transactions [10]. This encourages sellers to achieve more positive points by employing some fraudulent buyers and so the increased reputation enables them for more transactions (fraudulently). It is common in e-marketplaces in which people can rate a seller without making any transaction. Moreover, it is even possible in e-marketplaces in which rating is available only after a transaction, because they can make fake purchases. Simple solutions are adopted in e-marketplaces such as eBay in which for every buyer only one rating is taken into account. Although this method makes the attack more difficult but considering easiness of creating new IDs in these markets, it remains applicable.

1.2 Motivation

As described above, there are several challenges for e-marketplaces. Several works have been done to tackle these problems, but as will be discussed in the related work section, the most successful and strong works are those based on direct reward and punishment. However, all the previous works on direct reward and punishment focus on special purpose e-marketplaces and cannot be applied to most of the existing e-marketplaces. In this paper, we are focusing on providing a mechanism to face challenges of general e-marketplaces such as eBay. The exact definition of a general e-marketplace is presented in Sect. 3.1.

In the following, we explain the previously proposed direct reward and punishment methods and their limitations. The details of each method will later be explained in Sect. 2. Dellarocas [11] introduces the GWH method. This method assumes that each product is provided with different qualities and all qualities are acceptable by the buyer if the price is suitably determined thus it can be used just for special purpose e-marketplaces in which this assumption is correct. Tran and Cohen [9] have proposed another method which has the same drawback as [11]. Liu and Zhang [12] have proposed a method that is only usable in E-Marketplaces in which there is a Limited Inventory for a product or service (named as EMLI) and the method is not applicable to a general e-marketplace. Kerr and Kohen [7, 13] have proposed a method where the seller provides a sort of deposit before carrying out any transaction. This makes the business hard for those sellers who intend to have a large number of transactions because they must provide a large deposit. Li et al. [14] have proposed a method which is different from [7, 13] in some aspects but still suffer from the same problem. Vu et al. [15] proposed a method which is based on the assumption that the buyers would accept to pay more for exactly the same product in case that the seller has a higher reputation. This assumption is not applicable to general-purpose e-marketplaces.

1.3 Paper sections

In the rest of the paper, we present the related works including works related to trust and reputation systems and direct reward and punishment ones in Sect. 2. In Sect. 3, the proposed mechanism including market structure and the related definitions are explained in detail. In Sect. 4, the resistance of the proposed method resistance against the most common seller attacks in e-marketplaces is discussed. In Sect. 5, we explain more details of the parameter setting for the mechanism. In Sect. 6, an example market is provided, and the steps to find proper parameters are discussed. Using the example market, we have tried to show that the mechanism can work properly. Then we provide answers to some ambiguities in Sect. 7 and conclude the paper in Sect. 8.

2 Related works

The issue of trust management has been raised in several systems such as peer to peer (P2P) networks, content provision systems, service provider systems, electronic commerce systems and e-marketplaces. Some of the methods could be used only in one of these areas and some according to the general definitions of the agents and transactions can be used in different areas. In this section, to the possible extent, studies have been presented that can be used in e-marketplaces.

Stamoulis and Papaioannou [16] propose a method for providing the incentives for reporting truthful feedback in peer-to-peer systems. Swamynathan et al. [17] deal with main problems such as collusion and short-lived online identities in reputation systems used in P2P systems. Although several works have been done in the field of P2P systems, we focus on the works that are proposed to be applied in e-marketplaces.

The related works to the trust management systems can be divided into two major categories. The first category which is known as trust and reputation systems, mostly deal with receiving ratings and aggregating them to reach a reputation value for each agent. The second category, which can be called as direct reward and punishment methods, try to make the honesty the most profitable strategy for the agents. In the rest of this section, first we refer to trust and reputation related works. Then direct reward and punishment methods are explained.

One of the earliest works which can be considered as a trust and reputation system is the reputation system based on the β probability density function that has been proposed in [18]. This method estimates the seller's reputation based on a probability model. This model is based on the β probability density function that could be used to display the probability distribution of events [19]. This function with parameters of α, β, and p shows the relative chance of different values for the variable p. The variable p is a probability variable, so that for a given p the probability density $f(p|\alpha,\beta)$ represents second order probability. The first-order variable p represents the probability of an event, whereas the density $f(p|\alpha,\beta)$ represents the probability that the first-order variable has a specific value. However, due to the continuity of p in [0, 1], for a particular value for p, this would be very small value. Thus, usually, the mathematical expectation is calculated using the relation (1).

$$E(p) = \frac{m+1}{m+n+2} \tag{1}$$

For the application of the function on the reputation systems, n and m are the numbers of positive and negative points about a specific seller, respectively. For those who have recently entered the system and have no history, the mathematical expectation will be equal to 0.5. In contrast, consider a seller whose number of sales without fraud is less than the number of sales made fraudulently. In this case, the seller may prefer to exit the system and then to re-entering with a new ID (re-entry attack).

In some works such as [20] the issue of trust-scoring models has been considered, but from another viewpoint, some researchers are developing ways to deal with incorrect behaviors in online e-marketplaces which work based on the incentive compatible mechanisms. These methods mathematically check the interactions of individuals. These methods aim at making the correct and honest activity the most beneficial behavior for the commercial agents.

In the incentive mechanism provided by [21], a set of commercial agents act as brokers. These agents can buy the ratings of a seller from buyer agents and also sell them. Buyer agents first buy the ratings from the broker agents. After carrying out purchasing operation with the seller, the buyers can sell their ratings related to that seller to the broker agents from whom they already bought the rating. Payment to this buyer agent is made only when the provided rating is equal to the rating of the subsequent buyer that gives a rating to the same seller. If a buyer gives an honest score, his score is more likely to match the next person's rating. A simple two-agent example in this environment shows that the best strategy for an agent is to report the rating honestly because in this case, at least to 50% probability, he will be paid. In this mechanism, the system will maximize their total income when they both decide on being honest. This mechanism will not work properly if a large number of agents provide unfair feedback, or if they collude. Ghaffarinejad and Akbari [22] have proposed a similar method based on the brokers and buying and selling ratings. The main difference between this method and the previous method is the use of Specific Reputation Centers (SRC).

Braynov and Sandholm [23, 24] proposed a mechanism of trust disclosure which creates incentives for sellers to announce their reliability at the beginning of making a deal with a buyer. This mechanism includes a reliable buyer and probably an unreliable seller and works as follows. At the beginning of a transaction, the seller announces his reliability level. Then, the buyer announces the number of products that he is going to buy in this transaction. This number will be determined depending on the reliability announced by the seller. If this number is determined correctly, the seller will have sufficient incentives to announce his reliability correctly. This incentive mechanism works correctly when the cost of the seller for production have special features (including twice differentiability and being convex). However, this paper speaks only about the existence of such mechanism and does not present a practical mechanism. This method is not very useful because the buyers have less control on the number of products they want to buy. In fact, the number of products purchased by the buyer is determined not based on his actual needs but based on the reliability of the seller.

Hu and Lu [25] address the issue of bribery by sellers to consultants for providing unrealistic ratings and suggest forming a two-person repetitive prisoner's dilemma game to prevent it. In this type of game, the players adopt the cooperation strategy (i.e., honesty) to avoid the retaliation by others.

The second category of methods discussed in the literature is the methods based on the direct reward and punishment mechanisms. We use the term *direct* because they directly affect the utility of buyers or sellers. There are several parameters which these mechanisms control one or a set of them. These parameters include:

1. Authorizing/not authorizing to make a transaction.
2. The price of a good or service.
3. The profit and loss of a seller.
4. Number of goods or services sold in a transaction.
5. The quality of goods or services sold in a transaction.

Dellarocas [11] introduces the GWH method. The proposed system can be used in systems in which the seller offers a product with various qualities. This mechanism seeks to encourage the sellers to express the quality of their products honestly. The auction mechanism determines the price of a product. Sellers announce the quality of their product, but the e-marketplace does not announce the same quality to the buyer. In fact, the system, based on the comparison of quality announced by the seller and the quality announced by the buyer at previous transactions, announces the quality. The less quality announced by the system, the less bid by the potential buyers thus less profit for the seller. The announced quality is adjusted in such a way that the benefits achieved by the seller because of announcing unreal quality in past transactions are removed.

Tran and Cohen [9] have proposed a method based on reinforcement learning algorithms used by buyer agents to determine which seller to choose for doing transactions in such a way that their benefits are maximized. On the other hand, seller agents also use a similar algorithm to maximize their profits by setting prices and changing the quality of products delivered to the buyer. In this method, the reliability of a buyer to a seller is only based on their personal experience. Thus, it is not appropriate for a new buyer who has not enough experience with some sellers. Also, this method can be used only in systems in which products with a verity of different qualities are supplied, and the buyer can accurately calculate the quality of the received product.

Liu and Zhang [12] have proposed a method that is suitable for use in Electronic Marketplaces in which there is a Limited Inventory for a product or service (EMLI). Examples of this type of market are hotel reservation systems (especially in right areas and during holidays) or America’s dental reservation system. The main characteristic of these markets is that the number of supplied goods or services is less than the number of their potential buyers. In this method, the prices of goods supplied by sellers with higher reputation are higher. In this way, the profits of sellers with right behavior would be higher.

Kerr and Kohen [7, 13] have proposed a method where the seller provides a sort of deposit before carrying out any transaction. In fact, they introduce a virtual currency called Trunit. The process of using this virtual currency is defined as follows: Before a buyer purchases something from the seller, the buyer must obtain sufficient confidence in the seller. This confidence is determined based on the Trunit inventory of the seller. During the transaction, an appropriate amount of the seller’s Trunits will be deducted. After receiving the desired product or service, the buyer will evaluate them. If what is received is in accordance by what the seller announced before the transaction, the buyer will reflect his confirmation in the electronic market. In the case of buyer satisfaction, Trunits are returned to the seller. Moreover, some extra Trunits are paid to him as a reward. Amount of Trunits required for the transaction as well as its reward is determined based on the transaction price. The problem is that a new seller has no Trunit to start any activity in the market. To resolve this problem which is called the startup problem, the paper suggests that the new seller purchases some Trunit from the owner of the e-marketplace. Although the startup problem is solved, sellers who intend to perform large transactions on the site need to deposit a large amount in the electronic market. Kerr and Cohen [13] presented a complementary mechanism which adds a rather complex system that is a parallel market for buying and selling

Trunits which cause the use of this method to be difficult for many of the today's general electronic marketplaces.

Li and Zhang [14] have proposed a method that works by hiding the real information of the sellers (controlled anonymity). Also, similar to the method proposed in [13], the seller is required to insure (such as by depositing) that he has sufficient funds to pay the compensation. Accordingly, using the game theory and forming a two-person game, they suggest that honesty will be the optimal strategy for the players. However, the proposed method affects the market structure by applying the controlled anonymity mechanism. On the other hand, the way of determining the exact amount of compensation has not been determined. Moreover, in cases of honesty in providing ratings by the buyers, the method will work the same as the one presented in [13].

Vu et al. [15] proposed a method in which the participants should pay an initial fee for membership in the system to prevent the re-entry attack. In the proposed mechanism, sellers who commit a fraud in a transaction will not be introduced to the potential buyers in the subsequent transaction. Besides, for honest sellers, the products' prices offered to buyers will be higher than the price determined by the sellers. The performance of this method is based on the fact that if the sellers have more honest behavior in the market, they can sell their goods at higher prices. On the other hand, buyers are willing to pay more for buying from a better-experienced seller.

3 The proposed seller honesty promoting method

In the proposed method, we will introduce a direct reward and punish system which can be used in a general electronic marketplace. The term *direct* is used because this kind of system directly affects the utility of buyers or sellers. The direct reward and punish methods mentioned in the related works section, cannot be applied to a general e-marketplace. The problem addressed in this paper considers a general electronic marketplace in which many sellers and buyers are active. We present a mechanism in which honest behavior for the seller is the most profitable strategy by using an incentive-based method.

3.1 Market structure

In our proposed method, we intend to present a method for promoting honesty in general electronic markets. An identified example of general markets that has been addressed in [8, 10] is eBay [26, 27]

In this research, a general market is defined as a market with the following characteristics:

1. Some products (usually a lot and diverse) exist for sale.
2. There is a defined quality for each product or service (Any quality other than the defined one is not considered as acceptable by the buyer.)

3. There are several sellers of each product, and there is no monopoly for any seller.
4. Buyer observes the list of sellers and their prices before buying and can select among them.
5. Buyer has control over the number of needed products, and there is no force on him/her for the number of products to buy.
6. Buyer can announce his/her view about transaction result after a specified time interval.
7. Pricing is based on competition between sellers, and there is no requirement for announcing any specific price.
8. The price that is determined by a seller is shown to the buyer without any manipulation by the e-marketplace.
9. A seller pays a market fee to the owner of the electronic marketplace for each transaction, and the market determines this fee (percentage of the payment).
10. The commercial agents involved are only sellers, buyers, and the e-marketplace owner.

3.2 Definitions

In this section, some terms which are frequently used in the rest of the paper are defined.

- *Transaction status* after a transaction is made, a buyer reports the result of the transaction as honest or dishonest which is called the status of the transaction. In the implementation of the system, it is possible to add a dishonesty detector which has the duty of detecting incorrect status reports. In this case, we use the term *final* transaction status for the result of the dishonesty detector.
- *Dishonest transaction* a transaction at which the seller has been dishonest is called a dishonest transaction. Dishonesty happens when the product is not received by the buyer or what is received does not match the description of the product or service which is shown in the market. In this case, the transaction status is *dishonest*.
- *Market fee* In electronic marketplaces, there is usually a specified amount of money received by the market owner for each transaction which is often called fee or commission. In this paper, we use the term *market fee*, and it is always a coefficient to the transaction value. The market fee can have a value between zero and one.
- *Safe settlement* in our method, we do not apply the punishment in one transaction, but we distribute it among some consequent ones. So, we will assume that the seller will have a number of transactions in the future that the punishment will be applied to them, and the mechanism determines this number. The settlement is postponed to the time that this number of transactions has been made. The time at which we make the settlement is called the safe settlement time.

3.3 Transaction management process

In most cases, the market fee is a constant percent of the transaction price. In the proposed mechanism, we suggest that by dynamically decreasing or increasing the market fee, reward or punish sellers for honest or dishonest behaviors. Figure 1 shows the assumed process to apply the proposed mechanism starting from a transaction and ending at the calculation of the fee for the next transaction. The various steps of this process are elaborated below.

- *Transaction* A transaction is performed at this stage.
- *Payment* In this stage, a buyer makes a payment. The assumption is that the payment is transferred to the e-marketplace and e-marketplace transfers a part of the payment to the seller in the consequent.
- *Fee Deduction* In this stage, a part is deducted from the payment as the market fee. It is worth noting that the market fee is variable in this method and is calculated for each transaction. The mechanism for determining the market fee is explained in the next section.
- *Settlement* This mechanism decides whether the settlement with the seller is safe regarding confronting with dishonesty and re-entry attacks. If it is safe, the remainder (after deducting market fee) is paid to the seller, and otherwise, it remains with the e-marketplace to do settlement when it is safe.
- *Buyer's Report* If buyer receives its intended product matching with what was presented by the seller, he/she will report the transaction as honest. Otherwise, if the product is not received or what is received does not satisfy the expectation, the result is announced as dishonest. In this work, we assume that the buyer reports the result of the transaction honestly. This is the same as assumptions in several related works such as [7, 9, 13, 15].

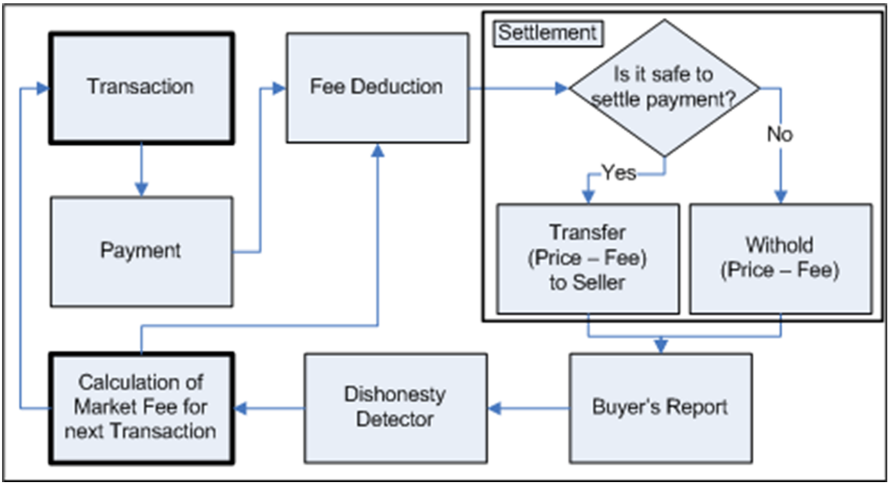

Fig. 1 Process of market transaction management

- *Dishonesty Detector* There is the possibility that while the buyer has received the product or service correctly, to rate the result of a transaction as negative in the e-marketplace or vice versa. We can assume that the buyer's report is always correct and adjust the fee based on that report (such as the assumption in [13]). On the other hand, to make it a bit more precise, we can feed the buyer's report to a trust and reputation system (similar to what is suggested in [15]). The system investigates the correctness of a buyer's claim and gives the proper result to the fee calculation mechanism. In the next sections, we will describe that there is the possibility of error in this part of the process, and the influence of this error on the mechanism performance will be explained.
- *Calculation of Market Fee for next Transaction* After analyzing the status of the current transaction, the market fee for the next transaction is calculated and specified based on the mechanism which is described in the next section.

3.4 Calculating market fee

For our mechanism to be resistant against dishonesty and re-entry, we need a function that has a higher value at the entry of a seller and decays to a minimum value (which is determined according to market owners' decision based on their profit and maintenance assumptions). We use an exponential function because this type of function has the property that decays very fast to its minimum value. For example, assume that the e-marketplace minimum acceptable fee is equal to 0.1 (which is equivalent to 10% of the transaction price). If a seller is forced to pay a higher fee for a lot of transactions at the beginning, he/she is discouraged participating in such an e-marketplace and moves to another one. So we intend to decrease the fee to the minimum fee (which is 0.1 in this example) faster in case that the seller is honest in his/her first transactions. It should be considered that the goal of the proposed method is not receiving a higher fee. We charge the seller with a higher fee just in his/her first transactions, and whenever a dishonest transaction occurs to prevent re-entry and dishonesty attacks. Section 4 elaborates on the ways the proposed function protects the e-marketplace against these attacks.

The fee for the *i*th transaction is obtained based on the following relation:

$$F_i = F_{min} + (F_I - F_{min}) * e^{-ir} + F_t * F_{SI} * e^{-jx} \tag{2}$$

where the parameters are: F_I: this parameter is the market fee in the arrival of a seller in the e-marketplace for his first transaction. During time and in the case of performing honest transactions by the seller, fee approaches F_{min}. F_{min}: this is the minimum acceptable fee from the e-marketplace owner's point of view. Logically, this parameter is determined to cover the costs of market maintenance and also the expected profit of the market owner. r: determines the rate at which the fee decreases. The larger the value of r, the quicker the fee approaches to F_{min}. As we are using an exponential function to determine the market fee, the value of the fee never reaches exactly to 0.1. So we assume approaching to 0.1 when it is less than 0.1001. Figure 2 shows market fee example charts in the case of honest behavior

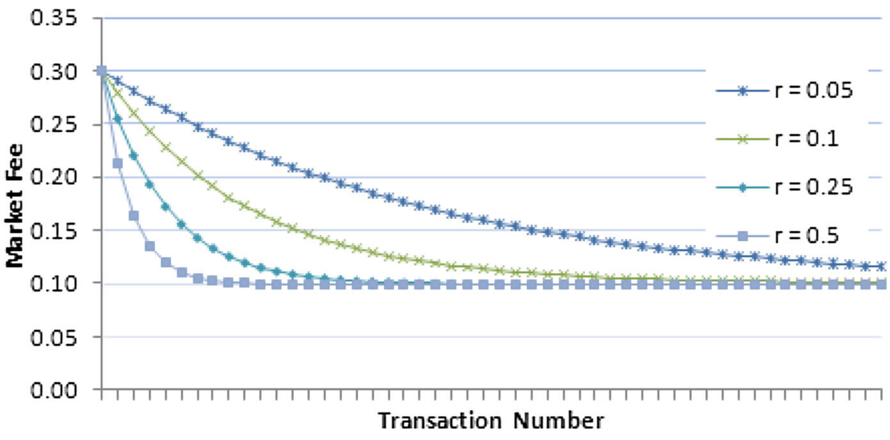

Fig. 2 Reducing market fee for different values of r

when assuming $F_I = 0.3$ and $F_{min} = 0.1$ for different values of r from 0.5 to 0.05. The fee approaches to the minimum value which in this case is 0.1 at 16th, 34th, 75th and 167th transaction for the values of r equal to 0.5, 0.25, 0.1 and 0.05 respectively. F_t: if the seller has done a dishonest action, F_t is the fee for the transaction in which the dishonesty has occurred. Otherwise, its value is equal to zero. F_{SI}: This is a coefficient that determines the punishment level in the case of a dishonest transaction. j: This parameter shows the number of transactions since the last dishonest transaction. The value of this parameter is initialized to one immediately after that a new dishonesty occurs. x: This is the speed of reduction in the level of punishment fee that is calculated at the occurrence of a dishonest transaction. In the next sections, its calculation method will be explained.

Figure 3 illustrates the change in the fee in the case of having a dishonest transaction. In this example figure, the parameters are assumed as $F_I = 0.3$,

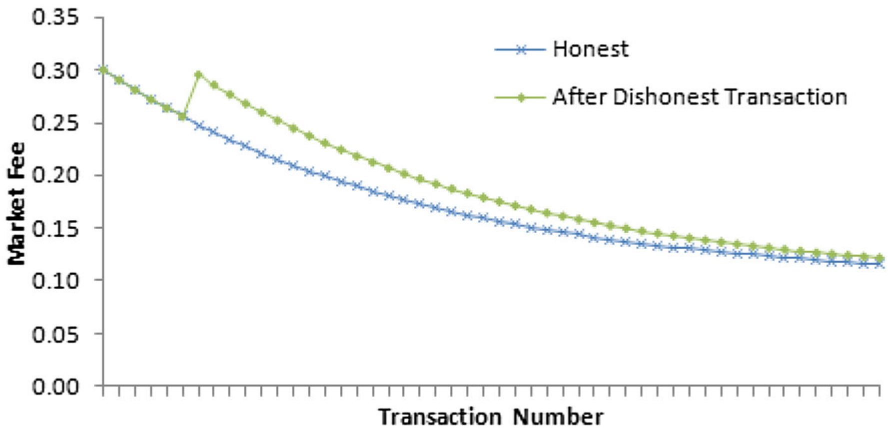

Fig. 3 The effect of a dishonest transaction (#6) on market fee

$F_{min} = 0.1$, $r = 0.05$, $F_{SI} = 0.2$ and $x = 0.5$. As shown in the figure, a dishonest transaction occurs at the 6th transaction. At this time the fee is 0.2558. So the F_t is equal to 0.2558. According to the above formula, the fee at 7th transaction becomes 0.2954.

3.5 Multiple dishonesty scenario

In Fig. 3, we only illustrated the single dishonesty by the seller. As mentioned before, F_t is the current total fee at the time of the dishonest transaction. Its value is the normal fee plus the punishment fee. After each dishonest transaction, F_t is used to change the market fee as it is shown in relation 2. The effect of multiple dishonesties in 6th, 20th and 30th transactions is depicted in Fig. 4.

4 Resistance against attacks and errors

In this section, we will deal with different attacks and errors which may occur in an electronic marketplace and the ways the mechanism makes the system resistance against them.

4.1 Resistance against dishonesty or cheating

Suppose a seller behaves honestly until the $(t - 1)$th transaction and intends to cheat in the tth transaction. $Profit_h$ shows the profit of n future transactions in the case of choosing honesty in the tth transaction. In the case of selecting dishonest behavior, the total profit is shown by $Profit_{dh}$. The following relations demonstrate the profit values where the P is the price of the product or service. The parameter P is the price of the product which is announced by the seller. The Pp parameter is the net profit percentage of the seller considering the cost of production, packaging,

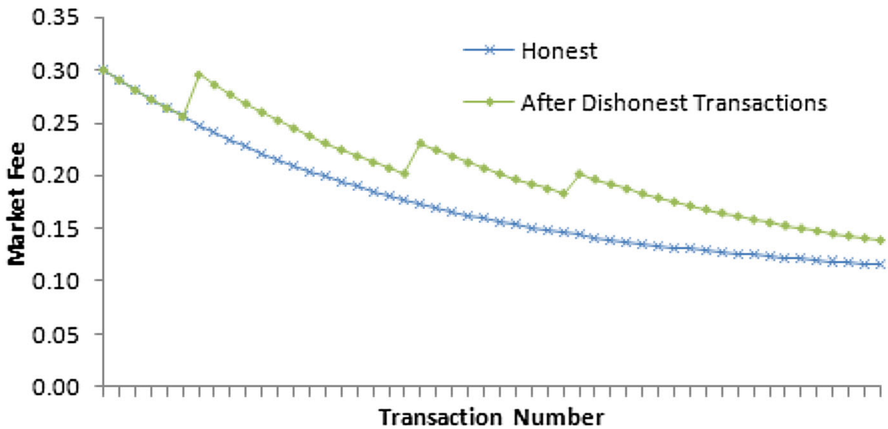

Fig. 4 The effect of a seller's multiple dishonesties (#6, #20, and #30) on market fee

shipping, etc. Thus $P_p = 1 - \frac{\text{Costofproduction,packaging,shipping,etc.}}{\text{Priceoftheproduct}}$. In the following formulas, the final value of the net profit is equal to P * Pp.

$$Profit_h = \sum_{i=1}^{n} \left[P * P_p - P * \left(F_{min} + (F_t - F_{min}) * e^{-ir} \right) \right] \quad (3)$$

$$Profit_{dh} = \sum_{i=1}^{n} \left[P * P_p - P * \left(F_{min} + (F_t - F_{min}) * e^{-ir} \right) - P * F_t * F_{SI} * e^{-ix} \right] \quad (4)$$

To make a dishonest behavior in the tth transaction not profitable for a seller, the difference between $Profit_h$ and $Profit_{dh}$ must be higher than abrupt profit from dishonesty, i.e., $P * (1 - F_t)$. In summary:

$$Profit_h - Profit_{dh} > P * (1 - F_t) \Rightarrow F_t * F_{SI} * e^{-x} * \frac{1 - e^{-nx}}{1 - e^{-x}} > 1 - F_t \quad (5)$$

4.2 Resistance against re-entry

After a dishonest behavior in the tth transaction, the seller may decide to register a new ID in the market to escape the punishment to be set by the market. The following relation shows the resulting benefit in the case of re-entry after the tth transaction.

$$Profit_{re} = \sum_{i=1}^{n} \left[P * P_p - P * \left(F_{min} + (F_I - F_{min}) * e^{-(i-1)r} \right) \right] \quad (6)$$

To resist against a re-entry attack, the following relation must be held.

$$Profit_{dh} > Profit_{re} \quad (7)$$

4.3 Simultaneous resistance against dishonesty and re-entry

For having a market resistant against both attacks at the same time, both the relations 5 and 7 must be held. Indeed, the parameters x and n must be determined.

According to the relation 5, the total punishment considered for the dishonest behavior is shown by P_t in relation 8.

$$P_t = \sum_{j=1}^{n} P * F_t * F_{SI} * e^{-jx} = P * F_t * F_{SI} * e^{-x} * \frac{1 - e^{-nx}}{1 - e^{-x}} \quad (8)$$

This level of punishment must be more than the profit from the dishonest action. Maximum profit happens when a seller does not send the product. It means that he/she receives the whole amount of payment and only pays the market fee.

$$P_t \geq P * (1 - F_t) \tag{9}$$

As relations 10 and 11 hold, concerning the limited values of F_t and F_{SI}, according to the intermediate value theorem we can be sure that by determining a proper value for n, there will always be a result for x if relation 12 holds.

$$\lim_{x \to \infty} P_t = 0 \tag{10}$$

$$\lim_{x \to 0} P_t = F_t * F_{SI} * \mathrm{n} \tag{11}$$

$$F_t * F_{SI} * \mathrm{n} > 1 - F_t \tag{12}$$

On the other hand, to make a dishonest transaction not profitable for the seller after re-entry, according to the relation 7, the following relations hold:

$$\frac{1 - \mathrm{e}^{-nr}}{1 - \mathrm{e}^{-r}} [F_t * \mathrm{e}^{-r} - F_{min} * (1 - \mathrm{e}^{-r}) - F_I] + \mathrm{P_t} < 0 \tag{13}$$

$$\frac{1 - \mathrm{e}^{-nr}}{1 - \mathrm{e}^{-r}} [F_I + F_{min} * (1 - \mathrm{e}^{-r}) - F_t * \mathrm{e}^{-r}] > 1 - F_t \tag{14}$$

If we suppose:

$$\mathrm{A} = \frac{1 - \mathrm{e}^{-nr}}{1 - \mathrm{e}^{-r}} [F_I + F_{min} * (1 - \mathrm{e}^{-r}) - F_t * \mathrm{e}^{-r}] \tag{15}$$

So:

$$\lim_{r \to \infty} \frac{1 - \mathrm{e}^{-nr}}{1 - \mathrm{e}^{-r}} = 1 \Rightarrow \lim_{r \to \infty} \mathrm{A} = F_I + F_{min} \tag{16}$$

$$\lim_{r \to 0} \frac{1 - \mathrm{e}^{-nr}}{1 - \mathrm{e}^{-r}} = n \Rightarrow \lim_{r \to 0} \mathrm{A} = n * (F_I - F_t) \tag{17}$$

So, according to the intermediate value theorem, if the two following relations are held, there is surely an answer for r:

$$(F_I + F_{min} < 1 - F_t) \mathrm{AND}\ \mathrm{n}(F_I - F_t) > 1 - F_t \tag{18}$$

4.4 Resistance against ballot stuffing

Sellers may try to collude with many non-real buyers to provide a high number of positive scores for themselves. As mentioned in [10], if the fee received by the market is more than the profit of a non-real positive score, this action is not cost-effective for the seller. Suppose a seller aims to do a fake transaction for obtaining a positive score. In our method, the reduction of the fee in the future transactions is the profit of a fake transaction for a seller. To determine the exact effect of the fake transaction, we assume that the seller is going to have m transactions in the market.

Relation 19 is the total fee paid for m real transaction and relation 20 is the total fee where one of the transactions is unreal, and the rest are real ones.

$$F = \sum_{i=0}^{m-1} \left[F_{min} + (F_0 - F_{min}) * \mathrm{e}^{-ir} \right] \tag{19}$$

$$\begin{aligned} F' &= \sum_{i=0}^{m} \left[F_{min} + (F_0 - F_{min}) * \mathrm{e}^{-ir} \right] \\ &= \sum_{i=0}^{m-1} \left[F_{min} + (F_0 - F_{min}) * \mathrm{e}^{-ir} \right] + F_{min} + (F_0 - F_{min}) * \mathrm{e}^{-mr} \end{aligned} \tag{20}$$

$$F_{min} + (F_0 - F_{min}) * \mathrm{e}^{-mr} > 0 \Rightarrow F' > F \tag{21}$$

Inequality in relation 21 always holds because the left-hand side of it is always positive for every value of m. Since $F' > F$, the seller will not have any incentive to perform a fake transaction. Therefore, the proposed method is resistant to ballot stuffing attack.

4.5 Resistance against value imbalance

As mentioned earlier, algorithms in which the value of the transaction is not considered are vulnerable to value imbalance attack when the trustworthiness of a seller increases. As the price of the transaction is always multiplied by the fee in our proposed mechanism, the only thing we need to consider is the different products or services prices from the same seller. To tackle this issue, we need to define a quantum for the price. For every transaction, depending on the number of quanta the price is, we should do a fast forward on the fee calculation.

4.6 Error in dishonesty detector

In previous sections, we assumed that the dishonesty detector is errorless and precisely reports the result of a transaction. But in reality, it may be not. In fact, it is possible that a dishonest action happens and it is evaluated as honest. This error will be desired for a dishonest seller because he/she has received the profit for dishonest action and has not incurred the resulting punishment. In this case, although a dishonest seller has profited, we can set a proper punishment at which the expected profit of the sellers remains unchanged.

Suppose that the probability of error in DD is P_{DDE}. The relation 22 is the seller's expected profit from dishonesty.

$$\begin{aligned} E(Profit_{dh}) &= P * (1 - F_t) + P_{DD} * Profit_h + (1 - P_{DD}) \\ &\quad * (Profit_h - P * (1 - F_t) - q) \end{aligned} \tag{22}$$

Parameter q is the extra punishment to compensate the DD error. If P_{DDE} is zero, the q will be equal to zero. Otherwise, the values of q should be chosen in a way that the profit remains unchanged:

$$q = \frac{P_{DD} * P * (1 - F_t)}{1 - P_{DD}} \tag{23}$$

5 Determining acceptable setting for market

For setting up this mechanism in an electronic market, it is necessary to adjust several parameters of the mechanism accurately. These parameters are F_{min}, F_I, r as discussed in Sect. 3.3. As discussed earlier, F_{min} is the minimum acceptable fee and should be chosen in a way to cover the costs of market maintenance and also the expected profit of the market owner. F_I must have a reasonable difference with F_{min} so that the re-entry is not profitable. In this section, we assume that F_{min} and F_I are selected, and we intend to choose a proper value for r. The following algorithm shows the steps to be done to determine the parameter r. Moreover, a list of acceptable (F_t, N) is prepared. Every pair of (F_t, n) where $n < N$ is considered as vulnerable.

Algorithm 1: Finding r Parameter

Input : R, Range of r

F_I, F_{min}, Initial and Minimum Fee

F_s, Fee steps

Output : Selected r

A list of acceptable (F_t, N)

1 foreach $r \in R$

2 foreach F_t values between F_I and F_{min} with F_s Steps

3 If there is at least one (x, N) pair to resist against both Dishonesty and Re-entry simultaneously (using the relations 5 and 7) then find N_m at which the fee reaches F_{min}

4 If N_m is acceptable then

5 store r for Output

6 store (F_t, N) as acceptable

First, r is selected from the determined range (e.g., between zero and one). Then, for each F_t that can be between F_{min} and F_I, we find an (x, N) pair that is simultaneously resistive against dishonesty and re-entry. If an (x, N) pair cannot be found, it shows that this r is not appropriate for correct implementation of the mechanism. According to the selected r, it can be determined that after how many transactions the fee reaches to F_{min} (N_m). Figure 5 shows the graph of N_m versus r. If this speed of fee reduction is acceptable based on the market owner preferences, the r is selected. It should be reminded that as we are using an exponential function to determine the market fee, the value of the fee never reaches exactly to 0.1. So we assume approaching to 0.1 when it is less than 0.1001.

6 An example market

In this section, first we will determine the proper mechanism settings for an example market, then the way the fee changes and the way parameter x is selected is explained through examples. In the end, by simulation, we will compare the profits made by honest and dishonest sellers, and we will show that being honest is the most profitable strategy for a seller.

6.1 Determining the acceptable parameters

As explained in Sect. 5, we should determine the values for F_I and F_{min}. For example market, we chose values 0.3 and 0.1 respectively. The next step is choosing a proper value for r. There are a lot of values for r that may fulfill the requirements for resistance against attacks. But, the value for r directly influences the parameter N (the expectation of seller presence in the market). It should be reminded that the payments of the seller are transmitted to the seller when the requirements for safety are fulfilled, and the safety is closely related to values for F_t and N.

Therefore, a proper value of r has a direct effect on how quick the payment is settled with the seller and thus the money turnover in the market. Figure 6 shows the minimum value for N for different values of r and F_t. In this figure, points with the values of N larger than 50 are not displayed as acceptable points. As shown, for large numbers of r (e.g., 0.2), just for a limited number of F_t a proper N can be

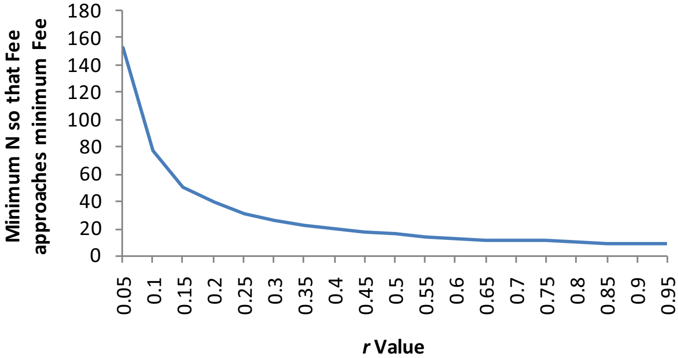

Fig. 5 The effect of the r parameter on the speed of almost reaching minimum fee

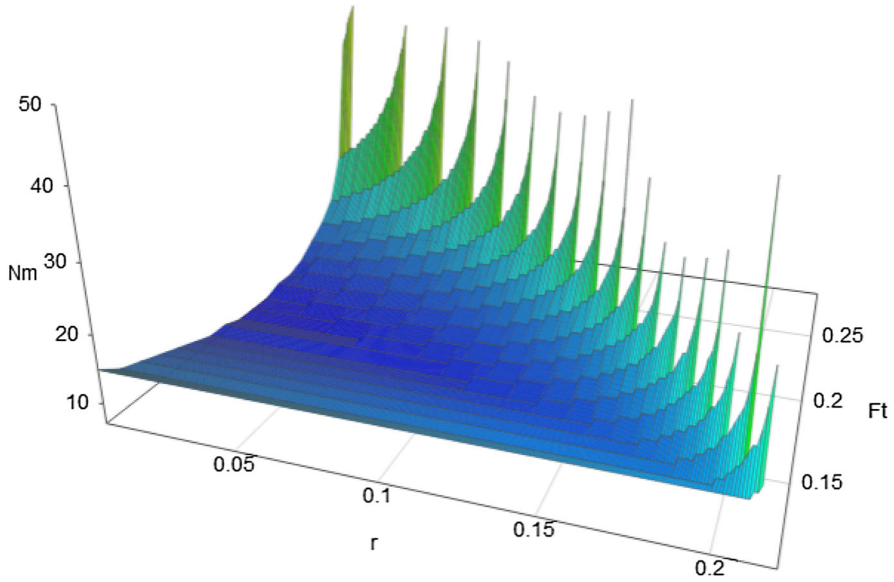

Fig. 6 Minimum of N to resist against Dishonesty and Re-entry attacks

found. So the preference is that we choose the value of the r parameter as small as possible. By considering Figs. 5 and 6, we selected the value of 0.1 for r.

The next step is selecting safe pairs for (F_t, N). These pairs should be kept as a list so that every time a payment is made, be settled if it is in the safe zone. Figure 7 is a sample list of safe pairs.

6.2 Simulation of the example market

A market with 100 sellers of ten different types and 1000 buyers was implemented. Every seller in every transaction selects a dishonest action with the probability of

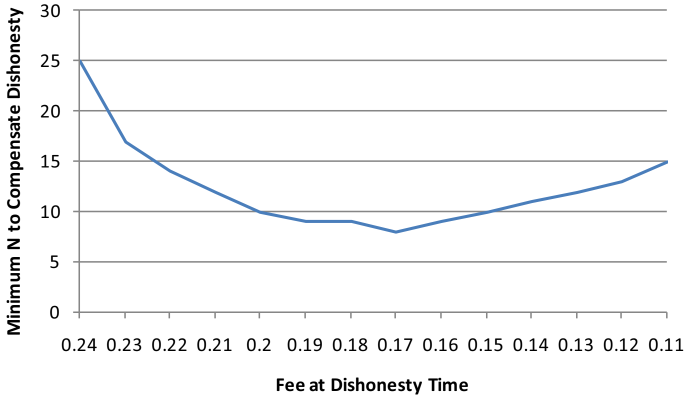

Fig. 7 The list of safe (F_t, N) pairs for the example market

5%. On the other hand, in the case of a dishonest action, commits a re-entry with the probability of 10%.

The Fig. 8 shows the profits of ten types of sellers in case of honest, dishonest and re-entry actions. The value of total profit in Fig. 8 is calculated as the sum of the total product prices minus the total fee which has been paid to the e-marketplace minus the total cost of the production, packaging, shipping, etc. (which is assumed to be a fixed value of 0.6 for all the provided results).

The first type (type 1 in the horizontal axis) is the seller with the least dishonest actions, and the last type (type 10) is the seller with the maximum probability of dishonest actions. In this figure, The *Total Profit (No Dishonesty)* is the total profit if the seller has been honest in all his transactions; the *Total Profit (No Re-entry)* is the total profit if the seller has been dishonest in some transactions but has not committed a re-entry; The *Total Profit* is the total profit if the seller has been dishonest in some transactions and has committed a re-entry after some of them.

As it was expected based on the mathematical proofs, the seller profit was maximized if honest actions were chosen. Additionally, if the seller acted dishonestly in a transaction, it is more profitable to continue with his current ID than committing a re-entry. On the other hand, the sellers with more probability of dishonest actions (types 8, 9 and 10) could have earned more by being honest.

7 Discussions

In this section, we try to address the theoretical and practical implications of applying our proposed mechanism and to provide answers to some questions that may arise about the mechanism. We also discuss the limitations of the proposed mechanism as future works of this research.

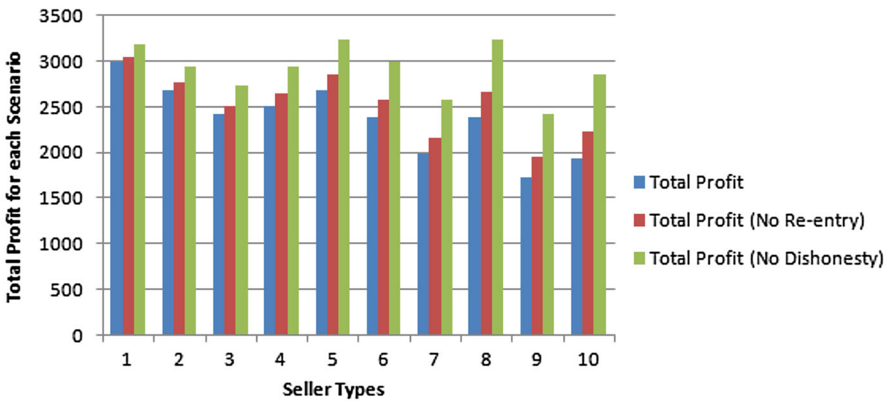

Fig. 8 Total profit of the honest and dishonest sellers

7.1 Assumptions and implications

In this research we assume that the e-marketplace receives fee for each transaction. Some example fee-based e-marketplaces are eBay, Amazon, Etsy and Asos. Thus, for e-marketplaces such as Alibaba who have a different revenue model, the method is not applicable. Another assumption of our research is that promoting honesty in an electronic marketplace will be beneficial for all three agents (i.e., seller, buyer, and e-marketplace owner). This is our main assumption similar to the papers we surveyed in Sect. 2.

Sulin and Pavlou [28] define trust as a catalyst in many buyer–seller transactions, and believe that trust can provide buyers with high expectations of satisfying. Pavlou [29] relates the trust to the perceived risk of consumers in an online market environment. The main managerial implication of deploying the proposed mechanism is that the dishonest behavior of sellers is not profitable. Thus, buyers are more satisfied and encouraged to make more purchases from such an e-marketplace because they will be less worried about the honesty of the sellers. This situation is also desired by the sellers because they will have more transactions, and consequently, more long term profit. As the e-marketplace operator/manager receives a fee for each transaction, an increase in the number of transactions will result in more fee and more profit for the e-marketplace operator/manager. Another management implication of such a mechanism is that unlike complicated trust and reputation mechanisms, before making a transaction, the sellers perceive the fee that they have to pay and this makes them directly, easily and immediately understand the effects of acting honestly or dishonestly.

Meanwhile, practically speaking there may be some issues that should be considered. First, there are sellers who do not understand the logic of the proposed e-marketplace, and therefore, they do not believe that being honest is the most profitable strategy for them. It may take some time for them to gradually learn the benefits of being honest in such an e-marketplace. As explained above, if they monitor the market fee which they pay in each transaction, they will realize that honesty has higher payoff than fraud. Another concern is that in the special cases that two or more sellers provide the same product/service with the same specifications (i.e., brand, quality, etc.), sellers may start a price competition which may affect the profit of sellers from an economic perspective, and consequently, their participation in such an e-marketplace. The detailed effect of competition and its pros and cons is comprehensively discussed by Stucke [30] and Porter [31] and is out of the scope of this paper.

7.2 Marketplace managers' incentives

One important question that needs further discussion is what would incentivize e-marketplace managers to deploy the proposed mechanism. This question should be dealt with from three different aspects.

First, regarding the number of transactions, applying this mechanism will increase buyers' trust in the e-marketplace, and consequently, the chance that they will choose this e-marketplace to buy a product or service. This will result in more transactions in the e-marketplace and more profit for the e-marketplace manager/owner.

Second, regarding the received fee, as explained before, the minimum acceptable fee is determined by the e-marketplace owner equal to the value of the market fee before adopting our proposed mechanism. So, the received market fee will never be less than before.

Third, regarding implementation complexities, it should be considered that only a few parameters such as i, j, F_t and x should be stored in a database for each seller. Moreover, the calculation of the fee is done using very simple formulas. Therefore, we believe that the implementation is very simple and needs very low extra computational resources.

7.3 Old sellers versus new sellers

In trust and reputation systems, the most important factor is the number of rating that a seller has received. In an e-marketplace which uses these systems, old sellers have more ratings in comparison with new sellers. Also, in case that old sellers have acted honestly in their transactions, they have higher ratings and are more recommended by the e-marketplace to the potential buyers, and therefore, it is very hard for new sellers to catch up. Unlike trust and reputation systems, in our mechanism, the only important factor is the honest action. The e-marketplace management system recommends both an old seller and a new seller in case they act honestly. Besides, as we use an exponential function to determine the fee, only after a few honest transactions, a new seller will pay a fee equal to the minimum fee and reaches exactly to the same state as an old seller.

7.4 Mechanism effects on seller selection by the buyers

The main purpose of this work is facilitating the selection of sellers by buyers, and the buyer is less worried about the honesty of a seller as the mechanism tries to guarantee that the seller himself will try his best to be honest in a transaction. But, as explained in Sect. 7.1, in practice, there are still some cases that the seller does not act honestly because they still do not understand the logic of the mechanism. As a result, although trust and reputation systems suffer from some unresolved attacks such as ballot stuffing, on–off attacks, discrimination, re-entry, etc., they can be useful to be used in parallel with the proposed mechanism. On the other hand, the review system which is implemented in some e-marketplaces can be useful for the buyer to choose a better item (not necessarily a better seller).

7.5 Comparison with escrow services

There are several methods to confront the risk of dishonest transactions. One of them is the risk transfer which is the assignment of a risk to a third party. This method is used in e-marketplaces with escrow services to transfer the risk to the market owner. Another approach is risk avoidance which is the elimination of hazards, activities and exposures that can negatively affect the e-marketplace. We have implemented the second approach in our work. In our proposed mechanism, we initially focus on the seller and try to make the sellers' honesty the most profitable strategy. In our approach, we aim to prevent dishonesty at the beginning as opposed to other methods in which it is applied after the transaction is made.

Nowadays, some e-marketplaces such as eBay adopt an escrow service to undertake the buyer's risk. On the one hand, most of the e-marketplaces, especially local and small ones, do not support this kind of escrow service. On the other hand, there are some complexities in using this service. As can be seen in eBay's "Money Back Guarantee" page [27], there are a lot of conditions for money back guarantee, and therefore, it is not granted in many cases. Moreover, there are several methods found on the web that a seller can skip the punishments.

7.6 Limitations of the proposed mechanism

The proposed mechanism suffers from the three major problems that needs further research.

First, as explained in Sect. 5, F_I must have a reasonable difference with F_{min} so that the re-entry is not profitable. There are some cases that the profit margin for an item is low and the payment of F_I is not acceptable by the seller. This fact should be considered by the market owner to find a proper value for F_I. Meanwhile, there are some cases that due to the very low profit margin, the proposed method is not applicable.

Second, the method assumes that the seller will have at least N more transactions (regardless of the identity he/she uses) which in some cases it is not true. Two examples are sales of used cars and art works.

Third, the method assumes that most of the buyers are honest when providing feedbacks for the transaction. In fact the effect of the dishonest buyers (which includes bad mouthing attack) on the seller utility is not taken into account.

8 Conclusion and future works

We proposed a reward and punishment mechanism that encourages sellers to be honest in all their transactions by adjusting the market fee. As the majority of e-marketplaces use commission fee revenue model, they can easily implement the proposed mechanism. We showed using mathematical proofs and simulation that by proper setting of the parameters of the proposed mechanism, the e-marketplace can become resistant against some very important attacks such as dishonesty and re-entry. On the other hand, as the mechanism works independently for every seller and is applied from the very beginning of the sellers' presence, it does not suffer from the initial window problem. Besides, unlike trust and reputation methods, our proposed mechanism considers the price of each transaction and deals effectively with value imbalance problem. An algorithm and an example market were provided to clarify the method and make it easier to implement so that every user of this mechanism can simply adopt it to the target e-marketplace. In the future, we will try to find solutions for the problems that we discussed in Sect. 7.6.

References

1. Bakos, J. Y. (1991). A strategic analysis of electronic marketplaces. *MIS Quarterly, 15*(3), 295–310.
2. Wang, S., & Archer, N. P. (2007). Electronic marketplace definition and classification: Literature review and clarifications. *Enterprise Information Systems, 1*(1), 89–112.
3. What is electronic marketplace? Definition and meaning. Available: http://www.businessdictionary.com/definition/electronic-marketplace.html. Accessed 12 December 2016.
4. Online marketplace. Available: https://en.wikipedia.org/wiki/Online_marketplace. Accessed 12 December 2016.
5. Malone, T. W., Yates, J., & Benjamin, R. I. (1987). Electronic markets and electronic hierarchies. *Communications of the ACM, 30*(6), 484–497.
6. Archer, N., & Gebauer, J. (2001). B2B applications to support business transactions: Overview and management considerations. In *Business to business electronic commerce: Challenges and solutions*. (p. 22).
7. Kerr, R., & Cohen, R. (2006). Modeling trust using transactional, numerical units. In *Proceedings of the international conference on privacy, security and trust: Bridge the gap between PST technologies and business services* (pp. 593–604). Markham, Canada.
8. Resnick, P., & Zeckhauser, R. (2002). Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. In *The economics of the internet and e-commerce*. Elsevier.
9. Tran, T., & Cohen, R. (2004). Improving user satisfaction in agent-based electronic marketplaces by reputation modelling and adjustable product quality. In *Proceedings of the third international joint conference on autonomous agents and multiagent systems* (Vol. 2, pp. 828–835). New York.
10. Bhattacharjee, R., & Goel, A. (2005). Avoiding ballot stuffing in ebay-like reputation systems. In *Proceedings of the ACM SIGCOMM workshop on Economics of peer-to-peer systems* (pp. 133–137). Philadelphia, PA, USA.
11. Dellarocas, C. (2002). Goodwill hunting: An economically efficient online feedback mechanism for environments with variable product quality. In *Proceedings of the international workshop on agent-mediated electronic commerce* (pp. 238–252). Berlin.
12. Liu, Y., & Zhang, J. (2014). An incentive mechanism designed for E-Marketplaces with limited inventory. *Electronic Commerce Research and Applications, 13*(2), 110–127.
13. Kerr, R., & Cohen, R. (2010). Trust as a tradable commodity: A foundation for safe electronic marketplaces. *Computational Intelligence, 26*(2), 160–182.
14. Li, Q., Zhang, J., & Martin, K. (2012). Feedback as "shadow of the present": An alternative to reputation systems for E-Marketplaces. In *Proceedings of the 11th international conference on trust, security and privacy in computing and communications* (pp. 334–341).
15. Vu, L. H., Zhang, J., & Aberer, K. (2014). Using identity premium for honesty enforcement and whitewashing prevention. *Computational Intelligence, 30*(4), 771–797.
16. Papaioannou, T. G., & Stamoulis, G. D. (2010). A mechanism that provides incentives for truthful feedback in peer-to-peer systems. *Electronic Commerce Research, 10*(3), 331–362.
17. Swamynathan, G., Almeroth, K. C., & Zhao, B. Y. (2010). The design of a reliable reputation system. *Electronic Commerce Research, 10*(3), 239–270.
18. Jøsang, A., & Ismail, R. (2002). The beta reputation system. In *Proceedings of the 15th bled electronic commerce conference* (Vol. 5, pp. 2502–2511). Slovenia.
19. Morid, M. A., & Shajari, M. (2012). An enhanced e-commerce trust model for community based centralized systems. *Electronic Commerce Research, 12*(4), 409–427.
20. Jurca, R., & Faltings, B. (2003). An incentive compatible reputation mechanism. In *Proceedings of the IEEE international conference on e-commerce* (pp. 285–292). Newport Beach: IEEE. http://ieeexplore.ieee.org/abstract/document/1210263/.
21. Beta Distribution Applet. Available: http://homepage.stat.uiowa.edu/~mbognar/applets/beta.html. Accessed 12 December 2016.
22. Ghaffarinejad, A., & Akbari, M. K. (2013). An incentive compatible and distributed reputation mechanism based on context similarity for service oriented systems. *Future Generation Computer Systems, 29*(3), 863–875.
23. Braynov, S., & Sandholm, T. (2002). Incentive compatible mechanism for trust revelation. In *Proceedings of the first international joint conference on Autonomous agents and multiagent systems* (pp. 310–311). Bologna, Italy.

24. Braynov, S., & Sandholm, T. (2002). Trust revelation in multiagent interaction. In *Proceedings of the workshop on the philosophy and design of socially adept technologies* (Vol. 2, pp. 57–60). Minneapolis.
25. Hu, J., & Lu, X. (2014). A reputation model of e-commerce based on iterated prisoner's dilemma game. In *Proceedings of the international conference on management of e-commerce and e-government* (pp. 24–27).
26. eBay Money Back Guarantee. https://pages.ebay.com/help/policies/money-back-guarantee.html. Accessed 12 December 2016.
27. EBay. Available: https://en.wikipedia.org/wiki/EBay. Accessed 12 December 2016.
28. Sulin, B., & Pavlou, P. A. (2002). Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quarterly, 26*(3), 243–268. http://www.jstor.org/stable/4132332.
29. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.
30. Stucke, M. E. (2013). Is competition always good? *Journal of antitrust Enforcement, 1*(1), 162–197.
31. Porter, M. E. (2006). How competitive forces shape strategy. *Strategic Planning: Readings, 2,* 102–117.