More Trusting, Less Trust? An Investigation of Early E-commerce in China*

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Abstract

Trust is vital for market development, but how can trust be enhanced in an online marketplace? A common view is that more trusting of buyers may help to build seller trustworthiness. This paper highlights a possibility that encouraging buyer trusting may *lower seller trustworthiness in equilibrium.* In particular, we set up a rational expectation model in which a marketplace uses buyer protection to promote buyer trusting. We show that it is possible for buyer protection to reduce trust in equilibrium and even hinder market expansion because it triggers differential entry between honest and strategic sellers and may induce more cheating from strategic sellers. Using a large transaction-level data set from the early years of Eachnet.com (an eBay equivalent in China), we find evidence that is consistent with this theoretical possibility. Stronger buyer protection leads to less favorable evaluation of seller behavior and is associated with slower market expansion. These findings suggest that a trust-promoting policy aiming at buyer trusting may not be effective if it is not accompanied by additional incentives to improve seller trustworthiness.

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1 Introduction

Despite rapid growth in the past twenty years, e-commerce faces a fundamental challenge in information. Because online traders are often far away and anonymous, buyers have doubts on whether sellers will deliver the goods as promised after receiving the payments. One way to overcome this information problem is online feedback: platforms like eBay have encouraged trading partners to leave feedbacks for previous transactions in the hope that reputation concerns will provide enough incentives traders to honor their promises. While reputation can be effective under the right conditions (Klein and Leffler, 1981; Shapiro, 1982, see a review by Bar-Isaac and Tadelis 2008), it is slow to build and subject to caveats such as incomplete feedback rate and strategic reporting (see reviews by Bajari and Hortacsu 2004, and Dellarocus 2003). In reality, many online platforms adopt other trust-promoting policies in addition to the online feedback system. One of the most widely used policies is buyer protection.

Unlike seller reputation which attempts to punish misbehaving sellers via less future trade, buyer protection targets buyer belief. For example, eBay promises that "If the item isn't exactly what you ordered, eBay will make it right by covering your purchase price plus original shipping on virtually all items."[1] Does more trusting from buyers always foster more trustworthiness on the seller side? In this paper, we show that the answer can be negative if buyer protection attracts more strategic sellers to enter and/or induce more cheating behavior from strategic sellers after entry. Intuitively, blind trusting by unsophisticated buyers invites dishonest sellers, which certainly does not help trust-building. However, even under rational expectation, we show both theoretically and empirically that a buyer-protection policy that aims to enhance trusting can lead to less trust and smaller market size in equilibrium.

We define "trusting" as a buyer's belief that a seller will deliver a high quality product, and "trustworthiness" as the likelihood that a seller will keep her promise to deliver a high quality product. In a rational expectation equilibrium, trusting is equal to trustworthiness and therefore the equilibrium "trust" is the probability that a transaction randomly sampled in a market involves a high quality product. To put it differently, trusting is about demand (affecting willingness to pay), trustworthiness is about supply (affecting willingness to deliver high-quality products), and trust is the equilibrium level where demand meets supply (rational expectation).

To organize our thoughts, we build a simple rational expectation model to understand how buyer protection triggers the reactions of buyers and sellers and thus affects the equilibrium trust and market size. In particular, the buyer protection policy promises buyers a "money back guarantee" should they be cheated by sellers. There are two types of sellers: honest sellers always deliver high-quality products, whereas strategic sellers choose between delivering high- or low-quality products. Buyers are heterogeneous in their valuation of high-quality products; sellers

[1] http://pages.ebay.com/ebay-money-back-guarantee/, accessed on July 10, 2014.

are heterogeneous in entry cost and production cost. If a seller delivers a low-quality product and the buyer reports it to the platform, the platform can reimburse the buyer and penalize the seller. Note that seller penalty and buyer reimbursement are not necessarily linked, as it depends on the platform's policy and enforcement ability.

Under certain conditions, we show that a marginal increase of buyer protection can reduce equilibrium trust. The idea is as follows. More generous buyer protection increases buyers' willingness to buy, and in response sellers raise prices. The resulting increase in expected profit motivates differential entry between honest and strategic sellers. In some scenarios, disproportionally more strategic sellers will be attracted to the market because their returns from entry increase more than those of honest sellers. Furthermore, strategic sellers decide on not only whether to enter a market but also whether to cheat after entry. In some situations, we can show that as price increases with stronger buyer protection, returns from cheating are larger so strategic sellers may be induced to engage in more cheating. Through both market entry and cheating after entry, buyer protection may reduce the equilibrium level of trust. As more generous buyer protection leads to lower trust, the probability of completing a transaction may be lower because rational buyers expect the negative effects of buyer protection on seller trustworthiness. If the effect on the completion rate is sufficiently strong, the market size may even decrease as more buyer protection is offered. We study several extensions of the model and find that the main results are robust to specific modeling assumptions. The key assumption behind our main results is that honest sellers have a cost advantage in producing high quality products over strategic sellers. This assumption seems to be natural, as honest sellers who by definition always honor their promises must have either direct or effective (after taking into account of moral value) cost advantages in producing high quality products.[2]

We conduct our empirical analysis in the early e-commerce of China. As a developing country with a legacy of a central-planning economy, China has long suffered from weak laws and severe fraudulence in the market. When Eachnet (an eBay equivalent in China) introduced e-commerce into China in 1999, it encountered an even worse trading environment than offline markets due to the anonymity of online transactions. In its early days, Eachnet experimented with multiple tools to boost trust, including buyer protection, seller feedback scores, and a

[2]Our model is closely related to the lemon market model of Akerlof (1970). In Akerlof (1970), high quality sellers may be priced out of the market due to adverse selection and their higher reservation value, thus an increase in price brought out by buyer protection can induce high quality sellers to return to the market. We extend the classic work of Akerlof by allowing heterogeneous sellers (honest and strategic) who make endogenous entry choices and product quality choices. In our model, as price increases with buyer protection, both honest and strategic sellers are more likely to enter the market. Once entered the market, strategic sellers can choose either to produce high quality products or to cheat, whichever fits them the best. With higher prices, strategic sellers can be more inclined to cheat. Thus, it is possible in our model that higher prices attract disproportionally more strategic sellers than honest sellers.

warning system, which offers us an excellent opportunity to link these policies to transaction outcomes and market development.

We examine a large transaction dataset from Eachnet.com. While feedback scores had been in place since the beginning of our sample (June 2001), Eachnet did not adopt buyer protection until October 2001. Its first protection policy offered buyers up to 3000 RMB per transaction, a coverage close to universal, as 98% of completed transactions were under 3000 RMB at that time. Eleven months later, Eachnet lowered the upper limit of reimbursement to 1000 RMB and introduced a deductible of 100 RMB per transaction. Thanks to these policies, not only did different products receive different treatments, the differential treatments also varied nonuniformly over time. This allows us to explore variations across product categories and identify the effect of buyer protection policies from the overall growth of Eachnet. Between the two buyer protection regimes, Eachnet started to issue warnings to traders who were found guilty upon their trading partner's complaint to Eachnet. Warnings could result in a complete ban on trading on Eachnet, effectively the only online trading platform in China at that time. We observe seller feedback and seller warning outcomes on the same transaction and use both to infer seller trustworthiness.

Our empirical analysis yields two main findings. First, when buyer protection is more generous, sellers are less likely to receive positive feedback and more likely to receive an Eachnet warning on a completed transaction. The negative effect of buyer protection on seller's positive feedback is found to be greater for high-value goods than for low-value goods, and more buyer protection is linked to lower completion rates and higher prices for completed listings. The second main finding relates buyer protection to market size, which is measured by the number of listings and sellers in each product category. A greater coverage of buyer protection is found to be correlated with a reduction in market size, suggesting that the negative effect of buyer protection on completion rate (due to buyer anticipation of lower trust) dominates its original encouragement of buyer trusting. These results provide supporting evidence for the insights from our theoretical analysis that buyer protection alone does not necessarily increase equilibrium trust and market size. Healthy e-commerce development requires more than increasing the trusting level by promising protection to buyers. Building institutions, especially a well functioning legal or market system that penalizes cheating sellers, is fundamental to ensure seller trustworthiness.

Our paper contributes to a growing literature on e-commerce. Most empirical papers in this literature focus on online reputation, for example the effect of seller reputation on completion rate and transaction price on eBay (as reviewed in Bajari and Hortascu, 2004 and Dellarocus, 2003), the dynamics of seller reputation in eBay (Cabral and Hortacsu, 2010; Fan, Ju and Xiao 2013), the experimental studies on reputation building (Bohnet and Huck, 2004), and ways to improve the feedback system (Bolton, Katok and Ockenfels, 2004). We are aware of only one published paper on buyer protection (Roberts, 2011), which uses transaction data from a US website for tractors and farm machinery to study whether buyer protection affects how seller reputation influences price and probability of sale. Roberts finds that buyer protection does not have significant effects, either because buyers are insensitive to small reputation differences or because buyers are skeptical of the protection program. In contrast, we investigate the effect of buyer protection on seller behavior and market size, both of which are not readily measured in Roberts (2011). Our theoretical and empirical results help us understand why a policy that targets buyer trusting can reduce trust and why trust is difficult to build in emerging markets. Another working paper (Hui, Saeedi, Shen and Sundaresan 2014) examines buyer protection on eBay. The buyer protection policy under their scrutiny is implemented by seller refund to complaining buyers and therefore is different from our setting.

Our paper is also related to a more general literature on the determinants of trust, which defines trust as beliefs or attitudes shaped by personal experience, community characteristics, and cultural environment (e.g. La Porta et al., 1997; Alesina and La Ferrara, 2002; Algan and Cahuc, 2010). In comparison, we consider trust an equilibrium interaction of trusting and trustworthiness. With rational expectation, our definition of trust can be directly measured by trade outcomes instead of opinion surveys or experiments (e.g. Glasaer et al., 2000; Resnick and Zeckhauser, 2002; Buchan and Croson, 2004; and Guiso et al., 2004). Our results highlight the importance of distinguishing trusting and trustworthiness, and suggest that a trust-promoting policy aimed at buyer trusting may not be effective if it is not accompanied by additional incentives to improve seller trustworthiness.

The rest of the paper is organized as follows. The next section describes the institutional background of Eachnet. Section 3 presents our model, and Section 4 describes the Eachnet data. The empirical results are reported in Section 5. A conclusion is offered in Section 6.

2 Institutional Background

2.1 Eachnet

Eachnet.com was founded in August 1999 and has been one of the largest consumer-to-consumer (C2C) and business-to-consumer (B2C) online trading platforms in China. As of April 2003 when our data ended, Eachnet had over 4 million registered users from all over China, and the annual market transactions amounted to 2 billion RMB. To a large extent, Eachnet was a Chinese version of eBay since it copied a host of chief features from eBay, including the feedback system, online auction, and fee charges on listing products and trading. Before the major rival of Eachnet, Taobao.com, emerged in 2004, Eachnet had a nearly 90 percent market share of C2C online transactions in China during 1999-2003. In June 2003, Eachnet was taken over by eBay and later on resold to TOM.com.

The biggest difference between Eachnet and eBay is that Eachnet lacks a secured online payment system due to the limited use of credit cards and the high cost of banking services in China. As a result, when a transaction is closed online, it constitutes an agreement between a seller and a buyer only on the product and price to be traded. To execute the transaction, individual traders have to go off-line to exchange money and the product. The standard procedure goes as follows: after a transaction is completed on Eachnet, Eachnet sends email messages to both the seller and the buyer, describing transaction details and contact information. Then the two parties contact each other through emails or phone calls and settle on how to pay and deliver. If both live in the same city, they may agree to meet and complete the exchange in person. If they are in different cities, typically the buyer sends the payment first and the seller mails the product after receiving the payment. Given China's weak legal enforcement of contracts, Eachnet transactions rely heavily on the trust-building institutions within the platform.

Eachnet's feedback score system was introduced in May 2001. Like eBay, the Eachnet feedback score is based on the feedback reported by trading partners. Feedback, which is solicited by Eachnet 3-30 days after the completion of an online transaction, has three potential forms: positive, neutral, or negative. If an individual receives a positive (negative) feedback, he or she will get one positive (negative) score. If the feedback is neutral, a trader's feedback score is unchanged. Just as on eBay, the accumulation of feedback score is linear: there is no distinction between a score earned from buying or selling and there is no weighting for the volume or product type involved in the transaction.

Eachnet's feedback score system is different from eBay's in two aspects: first, a registered user on Eachnet must pass a real identity check before trading and accumulating feedback scores. A government-issued ID card ensures genuine demographic information such as gender and region of residence. An ID check also makes it more difficult for an Eachnet trader to abandon an existing account and open a new one with a pseudonym. The second difference between Eachnet and eBay is how feedback scores are updated. Unlike eBay, which posts feedback whenever it is available, Eachnet publicizes buyer and seller feedback simultaneously one month after the closing date of a transaction. If one side does not provide feedback before the one-month deadline, Eachnet treats it as a voluntary omission and does not allow any subsequent change. This rule is designed to minimize concern over retaliation when reporting a negative experience.

2.2 Buyer Protection and Seller Warning

Eachnet implemented a buyer protection program in October 2001. Upon a buyer's complaint of seller cheating, Eachnet offered reimbursement up to 3000 RMB per transaction. This coverage was close to universal, as 98% of completed transactions were under 3000 RMB at that time. In September 2002, probably due to the sharply increasing burden of paying reimbursement claims, Eachnet lowered the reimbursement limit to 1000 RMB and imposed a deductible of 100 RMB per transaction. This system generated different degrees of buyer protection depending on the transaction price. Compared with the generous protection before September 2002, a buyer paying 1500 RMB for an item could be reimbursed only up to 1000 after September 2002, a buyer paying 500 RMB could be reimbursed 400, and a buyer paying 100 RMB or less got no protection at all.

In our subsequent analysis, we will focus on three regimes of buyer protection: 1) regime 0: zero coverage prior to October 2001; 2) regime 1: generous coverage from October 2001 to August 2002; and 3) regime 2: partial coverage in and after September 2002. Table 1 describes the two buyer protection policies by transaction price; Figure 1 plots the extent of buyer protection against transaction price by regime. The second policy, especially the variation in coverage of different values, is essential for us to identify the effect of buyer protection. In comparison, the first policy is close to full protection for almost all transactions; thus, its effect is not easily identifiable from the rapid market growth of Eachnet in the sample period. Equally important is the fact that the relationship between buyer protection and transaction price is non-monotonic and this non-monotonic relationship changes sharply between regime 1 and regime 2 (Figure 1). This helps us identify the effect of buyer protection from a fundamental influence of price on seller trustworthiness.

Eachnet's warning system was introduced in February 2002 to punish bad behavior. For any completed transaction, if one side feels mistreated by the trading partner, he or she can file a complaint with Eachnet. Upon receiving the complaint, Eachnet conducts an independent investigation. If there is clear evidence in support of the complaint, the trading partner receives a formal warning from Eachnet which is kept as a part of the trust history and visible to the whole market. However, if it is confirmed that the filed complaint is a serious misreporting or an ill-intended accusation, the complaining individual is punished by receiving a warning. An Eachnet warning carries no monetary fines, but a trader with three warnings must leave Eachnet. In this sense, an Eachnet warning is a threat to future activities and hence an implicit punishment for those who care about future access to Eachnet.

Eachnet's warning system was introduced for all transactions at the same time; thus, its impact is not identifiable from the overall growth of Eachnet. Instead of using Eachnet warning as a major policy treatment, we view seller recipient of an Eachnet warning as an indicator of seller behavior, which may differ from online feedback in two ways: first, the warning focuses on bad behavior but feedback can be positive or negative. Second, the warning involves a final judgment from Eachnet staff and can be linked to a reimbursement claim, while feedback reflects only one side's view and is independent of the official processing of the claim.

3 Theoretical Analysis

3.1 Basic Model

Consider a market (a trading platform such as Eachnet) where there are two types of sellers: honest and strategic. Only a seller knows his own type. In the population, the proportion of honest sellers is α in $(0,1)$. An honest seller always honors his promise by delivering a high quality product, which costs him c_H. A strategic seller honors his promise only when it is in his interest. We assume that it costs a strategic seller zero to produce a poor quality product, and his cost to produce a high quality product, denoted by c, is uniformly distributed on $(0, C)$. This implies that, if cheating bears no consequence, strategic sellers will produce poor quality. When a buyer receives a poor quality product, she will report to Eachnet with probability τ. For simplicity, we assume that buyers never misreport. Upon receiving the buyer complaint, Eachnet imposes a penalty $A \geq 0$ on the misbehaving seller. Thus, a strategic seller will cheat if and only if his cost of producing a high quality product c is greater than the expected penalty $n = \tau A > 0$. This implies that the inclination to cheat is most relevant for high-cost sellers. We assume $n < C$, otherwise no strategic seller will ever cheat.

In our empirical setting, seller penalty A includes an explicit warning from Eachnet (threat to deny future market access) and the implicit consequence of receiving one additional negative feedback (in terms of lower probability and/or lower price to sell in the future). In other settings, seller penalty may include legal liabilities and social condemnation. For simplicity, we do not model sellers' dynamic reputation building in feedback scores, but consider loss of reputation an element of the cheating penalty. We are interested in analyzing how sellers with identical feedback scores respond to changes in A.

A poor quality product has zero value to buyers, while the value of a high quality product v is uniformly distributed on $[V - e, V + e]$ with $V \geq e \geq 0$. The value of no trade is normalized as zero for the buyer. All buyers and sellers are assumed to be risk neutral.

Consider the following game:

- In stage 1, buyers and sellers decide whether to enter the market. To focus on seller entry, we assume that buyers have zero entry cost and that the entry cost of sellers, denoted by k, is uniformly distributed on $(0, K)$. Before entry, each seller knows his own type and entry cost, but strategic sellers do not know their costs of high quality products.[3]

- Having entered the market, each strategic seller knows his own production cost and each buyer knows her valuation. Then, in stage 2, buyers are randomly matched with sellers.

[3] We make this assumption to simplify the analysis of strategic sellers' entry decisions. In the alternative scenario when strategic sellers know their production costs before entry, it can be shown that our theoretical implications are qualitatively similar. Proofs are available upon request.

For simplicity, we assume that the critical masses of buyers and sellers are such that one seller is matched with one buyer.[4] The seller in each match announces a price p.[5]

- In stage 3, the buyer in a match decides whether to buy. If the buyer decides to buy, she pays the seller-announced price and the seller decides whether to produce a high or poor quality product. If the seller is of the strategic type and chooses to cheat, the buyer in this match reports to Eachnet with probability τ. Upon receiving the buyer complaint, Eachnet imposes a punishment A on the cheating seller and compensates the buyer's reimbursement claim equal to a fixed fraction w of the transaction price p, so that the total compensation is $I = wp$.

An equilibrium must satisfy three conditions: each seller makes optimal entry, pricing and quality decisions in order to maximize his (expected) net profit; each buyer makes an optimal purchasing decision; and each buyer's belief in the probability of receiving a low quality product reflects the actual probability of cheating in the marketplace.

At the pricing stage, we focus on one pooling equilibrium, where all strategic sellers mimic honest sellers in pricing; otherwise, buyers may believe that a seller setting a different price is a potential cheater and therefore avoid transacting with him.[6] In such a pooling equilibrium, honest sellers set an optimal monopoly price, and strategic sellers follow the suit. The model can be solved by backward induction, and the derivation is contained in Appendix A.

Let γ be the buyer's rational belief in the probability that the seller she is matched with will deliver a high quality product. Because of rational expectation, γ is also the proportion of high quality products in the market, thus a measure of actual trustworthiness. As shown in Appendix A, the equilibrium level of trust and the equilibrium price are jointly determined by the following two equations:

$$p(\gamma, V, e, \tau, w, c_H) = \frac{c_H}{2} + \frac{\gamma(V+e)}{2(1-(1-\gamma)\tau w)}, \tag{1}$$

[4]Our model can be extended to the case when one seller is matched with multiple buyers who compete in an auction to determine price. See Section 3.2.2 for details.

[5]Assuming that sellers set prices greatly simplifies our analysis. Alternatively, we can use the Nash Bargaining Solution to determine prices, where the trading partners divide the trade surplus according to their relative bargaining power. Our qualitative results should still hold under this alternative approach.

[6]In our model, those strategic sellers whose production costs of producing high quality products are above n will always cheat. If buyers hold the belief that a seller setting a price different from that of honest sellers is such a strategic type, then there will be no transaction. Hence such a deviation in price will not be profitable. So the pooling equilibrium can be easily supported. Note that there might be other equilibria with more complicated signalling strategies by sellers. However, those equilibria, if existing, would require highly sophisticated coordination among different kinds of sellers (with their signaling strategies) and buyers (with their rational beliefs), which are not likely to arise in the fast evolving early stage Eachnet market.

$$\frac{1}{1-\gamma} = \frac{\alpha(n - \frac{n^2}{2C} - c_H)}{(1-\alpha)(1-\frac{n}{C})(p - n + \frac{n^2}{2C})} + \frac{1}{(1-\alpha)(1-\frac{n}{C})} \tag{2}$$

Equation (1) is derived from sellers' optimal pricing decision, given buyers' trusting level γ. Plotting Equation (1) in a graph of p against γ, Figure 2 shows p as an increasing function of γ. This is because the more a buyer believes in high quality delivery (higher γ), the more she is willing to pay for the item, which motivates the seller to charge a higher price. Moreover, the more buyer protection there is (higher w), the greater the buyer's willingness to pay (conditional on γ), which encourages higher prices.

Equation (2) is derived from the equilibrium condition of rational expectation that, upon taking into account sellers' entry decisions, buyer belief in receiving a high quality product must be equal to the overall probability of sellers delivering high quality products. Note that $n - \frac{n^2}{2C}$ is the expected cost of a strategic seller, who will produce a high quality product when $c \leq n$ and will produce a poor quality product (and consequently receive a penalty n) when $c > n$. From now on we assume $c_H < n - \frac{n^2}{2C}$, i.e., the cost of an honest seller producing a high quality product (c_H) is lower than the cost of production that a strategic seller expects before entry ($n - \frac{n^2}{2C}$). This is easy to be satisfied when c_H is relatively small or n and C are relatively large. For honest sellers, they always honor their promises either because they have cost advantage of producing high quality products or because they attach high moral values onto being honest. Either way, we can interpret it as honest sellers have relatively small "effective" cost of producing high quality products, c_H.

Under this assumption, the numerator of the right hand side expression of Equation (2) is positive, so p is a downward sloping curve of γ (see Figure 2). This is because in rational expectation buyer belief in the probability of getting high quality depends on the ratio of honest and strategic sellers entering the market, and on the probability of strategic sellers honoring their promises (which is independent of price). Higher prices motivate both types of sellers to enter the market, but the effect is greater on strategic sellers under the assumption of $c_H < n - \frac{n^2}{2C}$. This can be seen from the following equation, which gives the relative ratio of honest to strategic sellers in the market:

$$R = \frac{\alpha(p - c_H)}{(1-\alpha)(p - n + \frac{n^2}{2C})}. \tag{3}$$

When $c_H < n - \frac{n^2}{2C}$, R decreases in p. Intuitively, if the expected cost of a strategic seller is greater than that of an honest seller, as the transaction price increases, the return from entry increases faster for strategic sellers than for honest sellers. Consequently, proportionally more strategic sellers will be attracted to the market following a price increase.

Under the condition $c_H < n - \frac{n^2}{2C}$, the intersection of Equations (1) and (2) in Figure 2 determines a unique equilibrium of the model. At the equilibrium, we have the following comparative statics (all proofs are contained in the Appendix):

Proposition 1 *When $c_H < n - \frac{n^2}{2C}$, the equilibrium level of trust(γ) decreases with buyer protection (w) and buyer's average value of high quality product (V), but increases with penalty on cheating behavior (A) and proportion of honest seller in the population (α).*

As shown in Figure 2, higher w moves curve (1) leftwards to (1') but leaves curve (2) unchanged, resulting in lower γ. In equilibrium, there is more cheating because relatively more strategic sellers are attracted to enter the market because more buyer protection increases buyers' willingness to pay and raises prices. Similarly, higher V motivates sellers to charge higher prices thus moves curve (1) to the left in Figure 3. Higher price leads to a lower ratio of honest to strategic sellers in the market (R), which reduces γ. This result suggests it is more difficult to sustain trust in a market of more valuable goods.

In contrast, greater penalty on cheating sellers (A) has a positive effect on equilibrium trust. In Figure 2, greater A shifts curve (2) rightwards to (2') but leaves curve (1) unchanged, leading to a higher p and a higher γ in equilibrium. Intuitively, the enhanced trust may come from two sources: first, stiffer penalty for cheating discourages strategic sellers from cheating; second, stronger punishment decreases the expected profit of strategic sellers, thus increasing the ratio of honest to strategic sellers (R) in the market. Lastly, higher α moves the belief curve from (2) to (2') in Figure 2, and thus increases γ in equilibrium. This is obvious. If a market has a higher proportion of honest sellers in the population, buyer's belief in getting a high quality product will increase, and so does the equilibrium level of trust.

Proposition 2 *When $c_H < n - \frac{n^2}{2C}$, the negative effect of buyer protection (w) on the equilibrium level of trust is more prominent for high-value products.*

From Equation (1), it is easy to see that the marginal effect of w on price increases in V. As w increases, the increase in price will be greater for more valuable goods, pushing curve (1) in Figure 2 further leftwards, resulting in even smaller γ. Intuitively, as compensation ratio increases, prices of more valuable goods will be raised higher, thus attracting proportionally more strategic sellers.

Proposition 3 *When $c_H < n - \frac{n^2}{2C}$, equilibrium price (p) increases with buyer protection(w), cheating punishment(A), buyer's average value of high quality products (V) and the proportion of honest sellers in the population (α).*

In Figure 2, greater w or V moves curve (1) leftwards and thus pushes up price; greater A or higher α shifts curve (2) rightwards and also leads to higher prices. These results are intuitive.

As shown in Appendix A, we can calculate the completion rate (the probability of a match resulting in a completed transaction) as follows:

$$CR = \frac{V+e}{4e} - \frac{c_H(1-(1-\gamma)\tau w)}{4e\gamma} \tag{4}$$

Proposition 4 *When $c_H < n - \frac{n^2}{2C}$, the completion rate (CR) increases with cheating penalty (A) and the proportion of honest sellers in the population (α).*

According to the above expression, everything else equal, greater γ leads to a higher completion rate. Since both A and α have a positive effect on γ, they have a positive effect on CR as well. Since w and V affect γ negatively, they also affect the completion rate negatively. However, conditional on γ, both w and V have direct, positive effects on the completion rate, thus their overall effects on CR are ambiguous. Nevertheless, as shown in the Appendix, it is not difficult to find parameter values such that the overall effect of w on the completion rate is negative.

Normalizing the total mass of potential sellers to one, we can define the market size (the proportion of honest sellers multiplies their entry probability plus the proportion of strategic sellers multiplies their entry probability):

$$MS = \frac{CR}{K}[p - (1-\alpha)(n - \frac{n^2}{2C} - c_H)] \tag{5}$$

The expression of MS has two parts: the first part is the completion rate CR; the second part is the average profit to be expected per transaction.

Proposition 5 *Under certain parameter values, the market size may decrease with the degree of buyer protection (w).*

As mentioned above, w can have a negative effect on the completion rate by lowering the trust level in the market but a positive effect on equilibrium prices. In the Appendix, we show that there are a non-trivial set of parameter values such that the negative effect can dominate the positive effect and thus the overall effect of w on the market size is negative. Thus, stronger buyer protection can lead to less market expansion! In our empirical analysis, we show that this indeed happened as Eachent introduced buyer protection schemes.

3.2 Extensions and Robustness

3.2.1 Variations in Cheating Behavior by Strategic Sellers

To make the model as simple as possible, we assume that strategic sellers all face the same expected penalty n. This implies that the probability of a strategic seller cheating is constant at $1 - \frac{n}{C}$ as long as the price is above n (otherwise strategic sellers would never cheat). Thus, the effects of buyer protection are driven solely from the differential entry between honest and strategic sellers.

The model can be easily extended to allow changes in cheating behavior of strategic sellers. Suppose the expected penalty a strategic seller faces if she cheats, n, is uniformly distributed on $[n_1, n_2]$ where $0 < n_1 < n_2 < C$. The randomness of n can come from either uncertainty about buyer reporting τ (different buyers may have different propensities of reporting cheating behavior) or randomness in reputation loss from the penalty A imposed by the marketplace (the same penalty may impose different costs to different sellers). For simplicity, suppose strategic sellers know about their expected penalty n at the same time when they know their production cost of producing high quality products. Then a strategic seller will cheat if $n < c$ and $n < p$. It is easy to show that the probability of a strategic seller cheating is $(1 - \frac{n_1+n_2}{2C}) * \frac{p-n_1}{n_2-n_1}$ when $n_1 < p < n_2$. It can be shown that all the main results of the basic model still hold in this extension.

With this extension, buyer protection does not only trigger differential entry between honest and strategic sellers, but also affect the cheating probability of strategic sellers after entry. From the expression of the probability of cheating by strategic sellers, strategic sellers are more likely to cheat with higher prices. Intuitively, as prices increase with stronger buyer protection, some strategic sellers who would not cheat at lower prices (when their expected penalty is higher than the price) will be attempted to cheat at higher prices (when the price exceeds their expected penalty). Simply put, higher prices mean greater returns from cheating, thus stronger incentives to cheat. Therefore, with stronger buyer protection, the proportion of strategic sellers engaging in cheating is larger. This additional effect reinforces the possibility that stronger buyer protection may lead to less trust. And with more reduction in the equilibrium level of trust, stronger buyer protection is more likely to lead to slower market expansion. [7]

3.2.2 Other Extensions

For simplicity, we assume that each seller is matched with one buyer. Our model can be extended to the case in which a seller is matched with multiple buyers. In such a case, buyers will compete in an ascending English auction. With identical and independent private valuation, this is equivalent to the second price auction in which buyers will bid their true valuation (as in a proxy bid). Let b be a bid for a buyer with a valuation of v for a high quality product. Then her expected valuation of a unknown quality product is $\gamma v + (1-\gamma)\tau w b$. Equalizing this with b gives $b = \gamma v / [1 - (1-\gamma)\tau w]$. Note that by standard auction theory, the buyer will set an optimal reserve price precisely as given by Equation (1), which is independent of the number of buyers. Thus, with multiple buyers, the realized price for a completed transaction is either the price given

[7] The solution to this extended model is available from the authors upon request.

by Equation (1) (when only one bid is above the reserve price), or $\gamma v_{(2)}[1-(1-\gamma)\tau w]$ (when two or more bids are above the reserve price), where $v_{(2)}$ is the second highest valuation. Taking the conditional expectation over $v_{(2)}$, we can see that the expected price in the latter case has the same properties as the price equation given by Equation (1), in particular, the monotonic relationship with regard to w.

The basic model can be also extended to incorporate more heterogeneity on either side. For example, suppose a proportion of buyers are naive in that they blindly trust all sellers. This will increase the overall willingness to buy in the market, and thus induce higher prices. As we have demonstrated, this may lead to lower equilibrium trust by attracting more strategic sellers to enter (and encouraging more cheating after entry), and possibly less market expansion. For another example, suppose there is another type of sellers who always cheat (producing high quality products is too costly for them). Then when prices rise with buyer protection, this type of always-cheating sellers will be attracted to the market. This will have an additional effect on equilibrium trust, further strengthening our results.

In Appendix B, we present a couple of additional extensions. One of them allows the platform to limit buyer protection reimbursement to the penalty gathered from cheaters (A). The other extension allows buyer reporting rate (τ) to increase with the coverage rate of buyer protection (w), which effectively increases the expected penalty ($n=\tau\cdot A$). Either extension will make the effect of buyer protection on equilibrium trust ambiguous, because the expected penalty for cheating is assumed to increase with buyer protection in both extensions. From the main model, we know the marginal effects of cheating penalty and buyer protection on equilibrium trust counteract each other, hence it is not surprising that the effect on equilibrium trust becomes ambiguous when an increase in buyer protection is tied with an increase in the expected penalty for cheating.

3.2.3 Robustness Issues

To summarize, we present a rational expectation model in which trust forms endogenously in an environment with buyer protection. We show that, when the production cost of honest sellers is lower than the expected production cost of strategic sellers, increasing buyer protection alone reduces equilibrium trust, and this effect is more conspicuous for higher-value items. Furthermore, under certain conditions, greater buyer protection may even lead to slower market expansion if its negative effect on equilibrium trust dominates.

These predictions are found to be robust to the extensions discussed above. However, they do hinge on the assumption that honest sellers have a cost advantage in production than an average strategic seller (i.e. $c_H < n - \frac{n^2}{2C}$). As mentioned before, the definition of honest sellers always honoring their promises suggests that they have "effective" cost advantage in producing high quality products, thus the above assumption seems natural. However, if this condition does not hold, higher transaction price may attract disproportionally more honest sellers to enter the market. This will change the belief curve in Figure 2 from downward sloping to upward sloping. As the price curve is upward sloping as well, the two curves could generate zero, one or multiple equilibria, which makes it difficult to characterize testable predictions.[8] In light of this, we emphasize that our theoretical analysis reveals an interesting theoretical possibility that buyer protection policies may lead to less trust and slower market expansion. Next we investigate empirically whether this actually takes place in the context of early e-commerce of China.

When bringing the theoretical insights from the model to data, a few words are needed to understand our model in a market with seller reputation. As a static model without seller reputation dynamics, our model can be viewed as describing how sellers with the same reputation (who thus appear identical in the eyes of buyers) behave in a market with imperfect institutions. To the extent that a bad transaction can penalize a seller via reputation loss, we may interpret penalty A as harm to seller reputation. However, in reality, seller reputation (e.g., feedback scores) can also signal to buyers the probability of the seller being an honest type. If so, higher seller reputation can imply a higher α. Fortunately, no matter how we interpret seller reputation in the real data, A and α tend to have similar effects on price (p), trust (γ) and completion rate (CR), although their effects on market size (MS) differ (positive for α but ambiguous for A).

4 Data

Our Eachnet data contain a random sample of roughly 100,000 sellers and track each seller's complete selling history from the seller's first listing on Eachnet (which dates back to as early as the start of Eachnet in September 1999) to the eve of eBay acquisition (April 2003). This sampling method allows a representative view of listings on Eachnet but we may miss a seller's buying history when he buys from sellers outside our sample.

For each product listing, we know whether it resulted in a completed transaction, where online completion means a buyer either agreed to pay the buy-it-now price or won the auction by offering a final price above the minimum price or the secret reservation price if such reservation existed. For each completed transaction, we observe four categories of information: 1) seller demographics including gender, age, income, occupation and region (if reported);[9] 2) seller history such as registration date, cumulative feedback score before the transaction, plus seller feedback and the Eachnet warning on this transaction if there is any; 3) buyer demographics (same as

[8]For the same reason, the condition we use ($c_H < n - \frac{n^2}{2C}$) is a sufficient but not a necessary condition for more buyer protection to lead to lower trust.

[9]For sellers, gender is the most frequently reported demographic (reporting rate 98.3%), as compared to age (10%), income (24.7%), education (49.5%) and occupation (19.5%).

that of the seller);[10] and 4) information on the listed product, pricing method (auction vs. fixed price), auction format, the transaction price and transaction closing time. Eachnet did not give us data on the exact text/picture description of an item or its bidding history.

For incomplete listings, we observe seller demographics and product information, but not buyer or transaction information.[11] One data challenge is that our raw data do not report the seller's cumulative feedback score before a listing if that listing was incomplete. However, since we know the seller's complete listing history, we first sort the data by seller id and listing time (detailed to second), and then impute the seller's feedback score as the same from his most recent completed transaction. Because we lack the seller's buying history, which could also contribute to seller feedback score, this imputation may introduce an upward or downward bias, especially if the seller's last completed transaction happened long time ago. We create a dummy equal to one if the time lag from the last completed transaction to the studied listing is more than 30 days, and control for this variable in all transaction-specific regressions. That being said, most of our key regressions are either conditional on completed transactions or based on a simple count of unique listings, and therefore do not need imputed seller scores.

Despite the lack of detailed item description, Eachnet classified each item into four levels of categories. The first level of category is the crudest; the second, third and fourth levels are more detailed progressively. For example, in the level-one category of cameras and camcorders, a level-two category is digital cameras, and a level-three category can be digital cameras that carry the brand Cannon. In total, our Eachnet data contain 20 level-one categories (including a residual category of "unknown classification"), 180 level-two categories, 669 level-three categories, and 692 level-four categories. Like "Cannon Digital Cameras", most level-three categories are not broken down further into more detailed level-four categories. Throughout the paper, we define market by level-two categories.

We focus on the sample period from June 1, 2001 to March 31, 2003 because the feedback score system was formally introduced in May 2001 and there is little information about trader behavior before the score system. We then rule out duplicates[12] as well as outliers that have

[10]Buyer information is not available until a transaction is completed. If a listing does not result in a transaction, we know the highest bidding price and the highest bidder's information. Conditional on completed transactions, the reporting rate on buyer demographics is 99.6% for gender, 25.8% for occupation, 45.1% for education, 29.3% for income, and 16.6% for age.

[11]An incomplete listing could contain buyer information about the highest bidder, if his/her bid does not meet the seller's secret reservation.

[12]In rare cases (less than 0.5% of the data), we observe multiple records that contain the same buyer id, same seller id, same product id, same listing time, and same closing time. One possibility is that the buyer purchased multiple units from the same listing but Eachnet counted it as multiple transactions. We collapse such duplicate records into one. In very few cases, these duplicate records report different feedback on the seller. When we collapse them, we define the seller feedback as positive/negative/neutral for this transaction if the average feedback across the duplicate records is positive/negative/zero. Including duplicated records in the final sample

transaction price, reserve price or listing price over 100,000 RMB. If a listing sells multiple units of a product and that listing leads to multiple transactions (with either different buyers or the same buyer at different close times), they appear as multiple records in the raw data. We keep them as separate transactions, but our count of unique listings only uses seller and listing information. This is why the number of records could exceed the number of listings in our summary statistics.

The final sample has 76,607 unique sellers, 1,291,902 unique listings, and 1,570,334 records, where a record is defined by the combination of seller id, product id, listing time, and if completed, buyer id and transaction closing time. On average, 53.48% of unique listings were completed with at least one transaction. Conditional on completion, 59.95% have final price at or under 100 RMB, 32.91% between 100 and 1000 RMB, 5.43% between 1000 and 3000 RMB, and only 1.72% above 3000 RMB.

Dividing the sample by three regimes of buyer protection, Table 2 presents regime-specific summary on market volume, listing attributes, completion rate, seller reputation at the time of listing, and feedback/warning outcomes. Over time, the number of listings grew rapidly. This trend is likely driven by faster growth in relatively low value items, as all prices used in listings – minimum, buy-it-now, or reservation price when it is available – tend to drop from regime 0 to regime 2. The big difference in various price measures between means and medians suggests that price distribution is positively skewed. Over time, sellers became more likely to sell newer items, list multiple items under the same listing, post pictures, quote buy-it-now prices, and become less likely to use bold fonts or auction.[13] As expected, seller scores increased over time, partly due to organic growth of reputation, partly due to the fact that reputable sellers are more likely to stay active in the market. Throughout the paper, we group missing, zero, and negative score as "fishy" scores. Completion rate increases significantly from 35.44% in regime 0 to 55.22% in regime 1 and then remains stable at 54.42% in regime 2.

Eachnet also expanded its categories over time: as of June 2001, active listings were observed in 133 of the 180 level-two categories and 300 of the 669 level-three categories. In March 2003, listings appeared in 172 level-two categories and 650 level-three categories. Given the fact that the number of level-three categories has increased more rapidly over time, most of our empirical analysis uses the level-two category to define specific markets and uses level-two category fixed effects to control for market-to-market variations. In special cases where we aim to predict an item's value as precisely as possible, we examine similar items that were listed before in the same and finest category.

The bottom panel of Table 2 focuses on completed transactions. Average final price dropped

does not affect our regression results.

[13]In our data, 80.88% of listings offer buy-it-now prices, and the percentage of auction-completed listing declines from 62.7% in regime 0 to 38.8% in regime 2. In our empirical analysis, we control for whether a listing has offered auction and/or buy-it-now, and whether it is completed by auction or buy-it-now.

steadily from regime 0 to regime 2, probably because lower-value items enjoyed faster growth. Thanks to the dramatic change in the buyer protection program, the extent of buyer protection – measured by the percent of final price covered by buyer protection – jumped from 0% in regime 0 to 99.04% in regime 1 and then dropped to 19.58% in regime 2.

In terms of seller feedback, sellers were more likely to receive any feedback in regimes 1 and 2 than in regime 0. Of all completed transactions, fewer and fewer sellers received negative feedback over time. The percentage of sellers receiving positive feedback increased sharply from 32.68% in regime 0 to 56.95% in regime 1, and then dropped slightly to 53.32% in regime 2. Figure 4 plots the monthly percentage of sellers receiving positive feedback throughout the 22 months of our analysis sample. A similar graph for the percentage of negative seller feedback is provided in Figure 5. These two percentages do not add up to one, because we count missing and neutral feedback as the residual group. Both figures show a strong and non-linear trend throughout the whole market, which highlights the importance of controlling for overall market growth (and other factors such as seller reputation and listing attributes). In both figures, we plot the data for four ranges of final price: below 100, between 100 and 1100, between 1100 and 3000, and over 3000. As the theory predicts, higher-value items are more likely to receive negative feedback and less likely to receive positive feedback.

Figure 6 plots the percentage of sellers receiving Eachnet warnings by month. Consistent with seller feedback, seller warning rate is higher for higher-value items. Its difference across price ranges increased to some extent after Eachnet revised its buyer protection policy in September 2002.

The last row of Table 2 shows that the likelihood of inter-region trading increases steadily over time, likely reflecting the geographic expansion of Eachnet and a greater willingness to trust long-distance trading partners. Our empirical analysis controls for the geographic region of sellers, and the geographic region of buyers if a listing is completed.

5 Empirical Tests

This section presents two sets of empirical results: one on transaction outcomes per listing, and the other on market size per product category. Towards the end of the section, we examine whether these empirical results are driven by across- or within-seller variations.

5.1 Results on Transaction Outcomes

5.1.1 Econometric specification and identification strategy

An ideal world to estimate the effect of buyer protection on market outcomes is to track two similar markets before and after one of them randomly adopts a buyer protection policy. In reality, we do have the before-after comparison but the buyer protection policy was adopted by Eachnet for the platform as a whole. Fortunately, in both regime 1 and regime 2, the buyer protection policy offers differential protection for different products. This implies that the intensity of "treatment" – measured by the percent of product value eligible for buyer reimbursement – varies by products. This enables us to compare product 1's outcome changes from no protection to x% protection with product 2's outcome changes from no protection to y% protection. Assuming the effect of a marginal percent increase of buyer protection is a constant for all products, we can identify the effect in a specification similar to that of difference-in-differences, where products subject to different degrees of buyer protection serve as "controls" for each other.

For this identification strategy to work, we need to consider a few alternative data-generating processes. First, Eachnet was growing rapidly during our sample period; we must distinguish the effect of buyer protection from this general trend. As long as the trend is common for all categories, we can control for it by year-month fixed effects and still explore the differential degree of buyer protection across products. This implies that the almost-universal buyer protection in regime 1 is not as useful in identifying the effect of buyer protection as the revision of protection benefits in regime 2. The second concern is that the degree of buyer protection is by definition a function of product value, but product value itself may have an impact on transaction outcomes regardless of buyer protection. This does not invalidate our differences-in-differences strategy, because the regime 0 data help us identify a fundamental relationship between product value and market outcomes before the introduction of any buyer protection. This argument is based on the assumption that the fundamental relationship does not change over time if the buyer protection had not been introduced. It is worth noting that the fundamental relationship between product value and market outcomes can be non-linear, so long as we have enough cross-sectional variations in regime 0 to identify this relationship. A more subtle issue is that the above two forces – the overall growth of Eachnet and the fundamental influence of product value – may interact. For example, the market of high- and low-value products may grow in different speeds, even if there were no buyer protection. As shown below, we address this concern by conducting a pre-treatment trend test for different produce value ranges in regime 0 data. In a robustness check, we also allow for a differential linear time trend by product value.[14]

In short, the above discussion leads to the following specification at the listing level:

$$Y_{istk}=\theta_w w_i+\theta_p f(V_i)+\theta_s S_i+\theta_c C_i+\theta_x X_i+\theta_b B_i+\alpha_t+\alpha_k+\epsilon_{it}. \tag{6}$$

where i denotes a listing, t denotes year-month, s denotes seller identity, k denotes market as defined by level-two category code, Y denotes transaction outcomes, ω denotes the degree

[14]The differential linear trend b product value can be identified separately from our key parameter on buyer protection because buyer protection benefits have fluctuated over time and the magnitude of their change is non-monotonic by product value.

of buyer protection, $f(V_i)$ denotes a polynomial function of product value V_i, $t \cdot V_i$ denotes the differential linear trend by product value, and $\{S, C, X, B\}$ denote seller attributes, market competition, listing attributes and buyer attributes respectively.

The remaining question is how to measure outcome Y, product value V, and the degree of buyer protection ω.

For outcome Y, our key theoretical prediction is on seller trustworthiness but we do not directly observe whether a seller has cheated in a transaction. What we observe are feedback and the Eachnet warning that a seller receives on a specific transaction. Assuming a buyer report is authentic, the probability of a seller receiving positive feedback is a product of the seller not cheating [15] and the buyer submitting positive feedback conditional on being treated well. Similarly, the probability of a seller receiving negative feedback is a product of the seller cheating and the buyer submitting negative feedback conditional on being cheated, and the probability of a seller receiving Eachnet warning is a product of seller cheating and buyer complaining to Eachnet conditional on being cheated. All four factors – seller behavior and the three buyer reporting probabilities – could change in response to buyer protection. Although we observe four outcomes for the same transaction, namely positive feedback, negative feedback, no/neutral feedback [16] and Eachnet warning, the first three must add up to one and therefore we only have three degrees of freedom, which is not enough to identify the effect of buyer protection on the above four factors.

One way to overcome this identification problem is assuming that buyer probability to submit positive feedback (conditional on good seller behavior) does not change with the buyer protection. This assumption is likely to hold because both buyer protection and Eachnet warning target misbehavior rather than good behavior. Nevertheless, it could be violated if buyers feel less need to contribute any feedback after the Eachnet introduced buyer protection and/or warning. As long as this change is universal across the market, it is absorbed in year-month fixed effects. To the extent that a buyer reporting positive feedback conditional on good seller behavior may be sensitive to the price she pays (or the value of the item), it has been addressed by controlling for product value as long as the reporting dependence on price/value does not change over time. With all these controls, the identification assumption we really need is that the probability of buyer reporting positive feedback conditional on good seller behavior does not change differentially by the degree of buyer protection. We believe this is a reasonable assumption because buyer

[15] In the model, we assume that every buyer pays because payment is embedded in buyer acceptance of seller offer. In reality, payment occurs after accepting the item online, which introduces the possibility that the buyer may be reluctant to complete the offline transaction if she spots any problem when she communicates with the seller. Because we do not observe buyer payment and seller delivery separately, under the assumption of truthful reporting, we refer to seller behavior as whether the seller fulfills his part of the transaction by communicating with the buyer and delivering the item as promised after receiving payment from the buyer.

[16] We pool neutral feedback as no feedback because it is rare and hard to interpret.

protection is irrelevant to the buyer if the seller behaves and the buyer report is truthful.[17]

Note that this assumption does not impose any restriction on the probability of reporting negative feedback or on the probability of complaining to Eachnet conditional on bad seller behavior; they could increase or decrease with the extent of buyer protection or the introduction of Eachnet warning. Indeed, changes in these probabilities could explain why the effects on seller's positive feedback, negative feedback and warning do not always mirror each other, even though they are based on exactly the same seller behavior.[18]

To measure buyer protection ω, we note that buyer protection coverage depends on transaction price but price is endogenously determined in equilibrium. Our solution is constructing a predicted price for each listing (denoted as $\hat{p}_i$) and using the predicted price to calculate expected buyer protection. In particular, for an item listed on day i in a finely-defined (level-four) product category, we look at all the previous listings in the same category that were completed in the closest five days before day i. The average transaction price of these previous listings is defined as the predicted price for this listing. Of all the 1,570,334 records in our sample, we are able to define valid predicted price for 1,223,991 of them (77.9%). Appendix Table 1 reproduces Table 2 conditional on having a valid predicted price. By definition, regime 0 has less history to calculate predicted price and therefore is less likely to have valid predicted price. Otherwise, most patterns in the sub-sample with predicted price are similar to the full sample. The predicted price also serves as a proxy for product value V.

Taking the above measurement issues into account, equation (6) can be rewritten as:

$$Y_{istk}{=}\theta_w w_i{+}\theta_p f(\hat{p}_i){+}\theta_s S_i{+}C_i\theta_c{+}X_i\theta_x{+}\theta_b B_i{+}\alpha_t{+}\alpha_k{+}\epsilon_{it}. \tag{7}$$

Conditional on completion, we use three dependent variables to measure seller behavior: whether a seller receives positive feedback, negative feedback, or an Eachnet warning on a particular transaction. Positive and negative feedback are mutually exclusive but do not add up to one because the seller may receive no or neutral feedback. Eachnet warning is independent of either positive or negative feedback.[19]

The extent of buyer protection w is calculated according to the price of the listing $\hat{p}$ and Eachnet buyer protection policy. In reality, Eachnet uses final price to determine w but final

[17] If the buyer misreports, she could receive an Eachnet warning.

[18] An alternative way to achieve identification is assuming the probability of buyer reporting feedback is independent of seller behavior. Even if this assumption holds for the days before Eachnet introduced buyer protection, it is unlikely to hold afterwards. Buyer protection clearly targets bad behavior and should affect the probability of reporting negative feedback more than the probability of reporting positive feedback.

[19] We do not take "any feedback" as a dependent variable because prob (any feedback) = prob (good seller behavior) * prob (positive feedback | good seller behavior) + (1-prob(good seller behavior))* prob(negative feedback | bad seller behavior). Given its dependence on seller behavior and two reporting rates, it is difficult to interpret the effect of a right hand side variable.

price is an equilibrium outcome. Since we do not observe the exact text, pictures, or format used in the listing, these unobserved product attributes could drive both final price and the outcome of seller feedback or Eachnet warning. To address this potential omitted variable bias, we calculate three versions of w by setting $\hat{p}$ equal to final price, buy-it-now price, and predicted price respectively.

As mentioned above, the control of $f(\hat{p})$ on the right hand side is meant to capture a fundamental relationship between product value and outcome that exists regardless of buyer protection. To the extent that buyer reporting probability differs by product value, it is also captured in the coefficient of $f(\hat{p})$. Since $f(\hat{p})$ is identified by the regime-0 data before any buyer protection, we have tried linear, quadratic and cubic functions in $f(\hat{p})$. Our main results control for quadratic $f(\hat{p})$; the results with linear or cubic $f(\hat{p})$ are reported as robustness check.

S denotes seller attributes such as the seller's Eachnet score at the time of listing, gender, region, and Eachnet age since registration.[20] Following the existing literature, we treat seller score as an indicator of seller reputation. Loss of reputation is one form of penalty for cheating sellers (A in the model), but it is difficult to judge whether the penalty is greater when a seller score drops from 100 to 99 than from 10 to 9. One can also interpret seller score as a proxy that signals (to buyers) the probability of the seller being an honest type, which corresponds to the population share of honest sellers (α) in the model. Because of this ambiguity, we refer to the coefficient of seller score as reputation effects. In some specifications, we include an interaction of seller score and a dummy of after-buyer-protection, to examine whether the reputation effect varies with the introduction of buyer protection. Similarly, we sometimes include an interaction of seller score and a dummy of after-Eachnet-warning.

C denotes competition from similar items on the Eachnet. To construct C, we first calculate the number of listings in the same finest category (up to four-level category code) in seven days before the listing date of the studied listing, and then divide it by the total number of view count on these listings (measured in thousands).[21] View count attempts to measure market demand for that fine category. In the model, we normalize buyer's outside option as zero. Empirically, C is a proxy for buyer's outside option.

X denotes a set of listing attributes such as whether the listing allows auction and/or buy-it-now, whether the listing has a reservation price, whether the listing posts a picture, whether the listing uses bold font, the seller-reported item condition, and other listing features.

B controls for buyer gender, buyer region, buyer's Eachnet score, buyer's Eachnet age,

[20] We calculated seller's cumulative number of completed listings before i, but its correlation with the seller's Eachnet score is higher than 0.95, so we do not control for it in the regression.

[21] We count the seven days conditional on having at least one completed transaction in that category. So these seven days could extend beyond one week before the listing. Since our listing time is detailed to days instead of hours/minutes/seconds, this calculation does not include listings that were listed on the same day as the studied listing in order to avoid contamination.

and whether the buyer and sellers are from the same region. Although these buyer attributes are transaction outcomes, they attempt to control for variations in buyer reporting rate. Many of them turn out to be highly significant, as female and experienced buyers are more likely to report and same-region buyers can better communicate with sellers and monitor them in the off-line part of the transaction. We tried the same specification without B, and the coefficients on key variables are qualitatively similar.

5.1.2 Results on seller feedback and warning

Appendix Table 2 reports the pre-treatment trend test on whether a seller receives positive or negative feedback on a single transaction. In particular, based on regime-0 data only, we take June 2001 as the default month and test whether seller feedback varies by the interaction of every other month of regime 0 and the three ranges of product values as defined by the buyer protection policy later on (0-100, 101-1100, 1100+). For robustness, we classify product value range by final price, buy-it-now price and predicted price separately and report the pre-treatment trend test for each measure. Month fixed effects and other controls are included. As shown in Appendix Table 2, all but one coefficients on the interaction term are insignificant from zero at 90% confidence. The only significant coefficient is not significant from zero at 95% confidence. These results suggest that within regime 0, seller feedback in different product value ranges followed a similar pre-treatment trend. This justifies our difference-in-differences strategy.

Table 3 presents regression results regarding whether a seller receives positive feedback on a single transaction. Columns 1-3 use final price to calculate degree of buyer protection, Columns 4-6 use buy-it-now price, and Columns 7-9 use predicted price. Under each measure of buyer protection, we report two specifications: the first reports a single coefficient of w; the second specification allows the coefficient of w to differ for $\hat{p}$ below and above 500 RMB; and the third specification allows seller score variables to interact with one dummy of after-buyer-protection and one dummy of after-Eachnet-warning. We report all results from a linear probability model, controlling for product category fixed effects (~180), seller region fixed effects (at the city level, ~24 as we consolidate small regions as one default group), buyer region fixed effects (~24), and year-month fixed effects (~22). Every specification also controls for a quadratic function of price.

In all specifications, we find that buyer protection has a significant, negative effect on the likelihood of a seller receiving positive feedback. Under the assumption that buyer reporting is authentic and the probability of reporting positive feedback conditional on good seller behavior does not change with buyer protection, this result confirms the theoretical possibility laid out in Proposition 1: sellers are less trustworthy when Eachnet offers greater buyer protection. In particular, the coefficient of w in Column 7 indicates that a change from no protection to full protection reduces the likelihood of seller positive feedback by 4.4 percentage points. This is a non-trivial effect as compared with the sample average of seller positive feedback (54%). Consistent with Proposition 2, we find a greater, negative effect of buyer protection on higher-value items. According to Column 8, the coefficient of w for $\hat{p} > 500$ is -0.066, which is 57% higher than that for $\hat{p} \leq 500$ (-0.042).

It is somewhat surprising that seller reputation – as measured by log(seller score if seller score >0) and a dummy of seller score being missing, negative, or zero (so called "fishy" score) – does not always have the expected effects. For example, Columns 1, 4 and 7 show that a fishy score relates to less positive feedback but log (positive seller score) also has an negative effect on seller positive feedback. Further examination shows that this is driven by differential effects of seller reputation before and after the introduction of buyer protection. Before the introduction of buyer protection (and Eachnet warning), higher (and positive) seller score did predict more positive feedback. However, both buyer protection and the Eachnet warning system weaken the incentive for reputable sellers to behave well. If we interpret seller reputation as A or α, this is consistent with the model prediction that buyer protection (w) and $\{A, \alpha\}$ could be substitutes or complements in their effect on trust.

Table 4 reports regression results of equation (7) on seller negative feedback and seller warning. Recall that buyer protection may generate changes in both seller trustworthiness and buyer reporting; thus, the prediction on seller negative feedback and seller warning are more uncertain. As we did for seller positive feedback, we report three sets of results for seller negative feedback, with buyer protection calculated by final price, buy-it-now price and predicted price respectively. For each measure of buyer protection, the second specification interacts seller score variables with a dummy of after-buyer-protection and a dummy of after-Eachnet-warning. These interactions cannot be identified for seller warning outcome, as Eachnet adopted a warning system after buyer protection. Hence we only report three columns of seller warning results.

Most of Table 4 is consistent with seller behavior inferred from Table 3: greater buyer protection is related to more seller negative feedback and more seller warning; higher log (seller score) is related to less negative feedback and less warning; having a missing/negative/zero seller score is related to more negative feedback and more warning. The only exception is the negative coefficient of w on seller negative feedback, where w is calculated by predicted price.[22] One possible explanation is that mistreated buyers tend to complain to the Eachnet warning system instead of reporting negative feedback.

Table 5 reports several robustness checks on the positive feedback regression: Column 1 controls for linear price instead of quadratic price, Column 2 controls for cubic price, Column 3 adds in a linear time trend of price (i.e. $\hat{p} \cdot t$) , and Column 4 has both cubic price and the linear time trend of price. The key coefficients on buy protection, seller reputation and their interactions are similar to what we have shown in Table 3. Similar robustness exists for the

[22]Further examination suggests that this coefficient is particularly driven by items with smaller values ($\hat{p} \leq 500$).

negative feedback regressions, we do not report them here in order to save space.

5.1.3 Results on completion rate and final price

Completion rate and transaction price are intermediate steps when the model analyzes the effect of buyer protection on trust. In particular, buyer protection is predicted to have a positive effect on price (Proposition 3) and an ambiguous effect on completion rate (Proposition 4). To test these predictions, we estimate:

$$1_{completed,istk} = (\alpha_{2s}) + \theta_{2w} w_i + \theta_{2p} \hat{p}_i + \theta_{2s} S_i + C_i \theta_{2c} + X_i \theta_{2x} + \alpha_{2t} + \alpha_{2k} + \epsilon_{2it}, \tag{8}$$

$$log(p_{istk}) = \theta_{3w} w_i + \theta_{3s} S_i + C_i \theta_{3c} + X_i \theta_{3x} + \alpha_{3t} + \alpha_{3k} + \epsilon_{3it}. \tag{9}$$

Right hand side variables follow Equation (7) with three exceptions: first, we use only predicted price to calculate buyer protection, because either final or buy-it-now price can be interpreted as transaction outcomes;[23] second, we do not include buyer attributes as they are not available for incomplete transactions and are jointly determined with price if they are available; third, we do not control for predicted price in the price regression because predicted price by definition aims to predict transaction price for that listing.

Table 5 presents linear regressions results for both completion rate and log final price. Because one listing may list multiple units of the same item and lead to multiple transactions, our unit of analysis is per unique listing for completion rate and per transaction for log price. We count a listing as completed if it leads to at least one complete transaction.[24] The price regression clusters error by listing id. In the even-numbered columns, we interact seller score variables with the after-buyer-protection and after-Eachnet-warning dummies.

Throughout the columns, we find that buyer protection always has a negative effect on completion rate and a positive effect on log price, both of which are consistent with our model. If the model is correct, a negative effect of buyer protection on completion rate implies a negative effect on market size, because buyer anticipation of worse seller behavior hurts the probability of sales and therefore discourages sellers from listing in the market. We will test this prediction in the next subsection.

Consistent with the previous e-commerce literature, the log of positive seller score increases completion rate and log price, while having a negative, zero or missing score reduces probability of sale. Surprisingly, sellers with a negative, zero or missing score also enjoy a price premium,

[23] While not reporting, we have rerun completion rate regressions by adding a quadratic term of predicted price on the right hand side. This specification does not change the sign (or magnitude) of the coefficient of w but increases its standard errors. This coefficient is no longer significant in Columns 1 and 3, but remains significant with p-value less than 0.05 in Columns 2 and 4, if we reproduce Table 5 under this alternative specification.

[24] In an alternative specification, we redefine completion as one if all records related to the listing are coded as completed transactions in our raw data. This alternative definition produces similar results.

compared to those with a reputation score of one. A possible interpretation is that sellers with inferior records target high-price items even though the chance of completing the transaction is small. As shown in Tables 3 and 4, "fishy" sellers do get more negative feedback, less positive feedback, and more warnings if their listings are completed.

The effects of "fishy" seller scores on completion rate and price become more conspicuous after the introduction of buyer protection and Eachnet warning. One explanation is that, over time, fewer and fewer sellers have "fishy" scores, which makes "fishy" scores more alarming to buyers and forces "fishy" sellers to charge high prices to a few gullible buyers. The effects of log positive seller score also change after the introduction of buyer protection and Eachnet warning. In particular, the positive effect of log seller score on completion rate is weakened after buyer protection and Eachnet warning, but its effect on price is positive only after the two program changes. Combined with Tables 3 and 4, this suggests that the role of seller reputation has changed from indicating reliable and trade-worthy sellers in regime 0, to facilitating higher price in regimes 1 and 2.

5.2 Market Size

Within the Eachnet data, we define each two-level category code (k) as a separate market. Among a total of 180 categories, 116 have at least one listing completed by the first month of our analysis sample (June 2001). In light of this, our study of market size focuses on the development of these 116 markets since July 2001, while taking each market as of June 2001 as the initial condition. In particular, we estimate:

$$N_{kt} = \theta_w w(\bar{p}_{k0}) + \alpha_t + \alpha_k + \epsilon_{it} \tag{10}$$

where k denotes product category, t denotes year-month, $\bar{p}_{k0}$ denotes market k's average transaction price in June 2001, and $w(\bar{p}_{k0})$ is the degree of buyer protection one would expect category k to have over time assuming the average value of potential listings remain at $\bar{p}_{k0}$. We do not control for $\bar{p}_{k0}$ directly because it is absorbed in category fixed effects (α_k).

The dependent variable – market size N_{kt} – is measured by log of the total number of listings, the total number of listed units, and the total number of unique sellers.

The key coefficient, θ_w, is identified from the overall market growth (controlled by year-month fixed effects α_t) because buyer protection policy differs by item values and changes non-monotonically over time. More precisely, θ_w is identified by a difference-in-differences strategy where different product categories received different treatment as the buyer protection policy changed over time. One assumption behind this identification strategy is that the trend of market growth is comparable across categories of different product value. Appendix Table 3 tests this assumption by using regime 0 data only and regressing various dependent variables on the interaction of each month dummy and the three ranges of $\bar{p}_{k0}$ (0-100, 101-1100, 1100+). The default is the first month (June 2001) in regime 0. None of the interaction terms are significant from zero, suggesting that the pre-treatment trends are comparable across different ranges of product value before the introduction of buyer protection.

Recall that our model makes an ambiguous prediction on the effect of buyer protection on market size: on the one hand, protection from the platform makes buyers more willing to transact at a given price and a given belief of seller trustworthiness; on the other hand, if buyer protection reduces equilibrium trust, rational buyers anticipate this negative effect and adjust their belief accordingly. When the latter dominates the former, buyer protection reduces completion rate and market size. Table 6 illustrates the negative effect of buyer protection on completion rate, so we expect buyer protection to reduce market size. As reported in Table 7, the regression results show that an increase in buyer protection has a large and significant negative effect on market size. There are two panels in Table 7: the first panel uses the 116 categories that exist throughout the sample; the second panel expands to the full sample with all 180 categories. Results are similar across the two panels, which suggests that the market shrinking effect of buyer protection is not driven by the addition of new markets on Eachnet.

5.3 Cross- and Within-seller Variations

The above evidence suggests that the detrimental effects of buyer protection on trust and market size are not only a theoretical possibility, but also a disturbing fact in the early development of Eachnet. This explains why Eachnet downgraded its buyer protection program substantially in September 2002. A remaining question is whether the detrimental effect of buyer protection on seller trustworthiness is driven by cross- or within-seller variations.

By cross-seller variations, we mean variations generated by sellers entering or exiting Eachnet. If buyer protection encourages dishonest sellers to enter and honest sellers to leave, it could explain the reduction in trust and market size. Alternatively, trust and market size can be reduced if buyer protection encourages the same sellers to become more strategic. A distinction of these two mechanisms can help us better understand the observed effects of buyer protection, but we are reluctant to label within-seller variations as moral hazard and cross-seller variations as adverse selection because a seller may intend to behave differently in two listings even before any buyer comes by.

As shown in Section 3, theory suggests that the negative effect of buyer protection on trust could be driven by relatively more entry of strategic sellers and a greater likelihood to cheat after entry. These two mechanisms correspond to across- and within-seller variations, but with a caveat: our theory focuses on one market and all predictions are derived from comparative statics; in the real data, after a seller enters Eachnet, he can choose which category to list in and therefore there could be category-specific entry and exit within a seller. Statistically, these category-specific entry and exit contribute to within-seller variations rather than cross-seller variations.

With this caveat in mind, we rerun the positive feedback regression with seller fixed effects, and report the new results in the first two columns of Table 8. To save space, we only report the regression where buyer protection is calculated by predicted price.[25] Comparing Table 8 with Table 3, we find that the coefficients of buyer protection are of the same sign and similar significance after we control for seller fixed effects, while their magnitudes drop roughly 11%. This suggests that the worsened seller trustworthiness in response to buyer protection is driven by both cross- and within-seller variations, but the within-seller variations are of greater importance.[26]

The last four columns of Table 8 report completion rate and price regressions with seller fixed effects. Within the same seller, greater buyer protection is still found to be associated with a significantly lower probability of sale and higher final price. This suggests that buyers anticipate the same seller to become more strategic in face of greater buyer protection, and therefore are more reluctant to complete the transaction.

Results with and without seller fixed effects reveal some interesting patterns regarding seller reputation. Without seller fixed effects, Tables 3 and 6 show that seller reputation predicted better seller feedback and higher probability of sale in regime 0, but these indicative effects were weakened after Eachnet introduced buyer protection and warning. When we add seller fixed effects (Table 9), the coefficient of log seller score is positive for seller positive feedback in all regimes. Although the interactions of log seller score with after-buyer-protection dummy and after-warning dummy are still negative, their weakening effect is not as large as in the regression without seller fixed effects. In comparison, the coefficient of log seller score in the completion regression, though still positive, is much smaller and sometimes even insignificant if the regression includes seller fixed effects. Turning to the price regression, if we do not include seller fixed effects, log seller score does not link with higher price until Eachnet introduced buyer protection or warning. However, when we include seller fixed effects, log seller score is significantly correlated with higher price, although sellers with fishy scores still tend to get higher price. Like in the regression without seller fixed effects, these effects did not show up significantly until Eachnet introduced buyer protection and/or seller warnings.

These estimates suggest that the positive correlation between better seller reputation and seller positive feedback (conditional on completion) is mostly driven by with-seller variations, while the positive correlation between better seller reputation and higher completion rate is

[25]Defining buyer protection by final or buy-it-now price yields similar results.

[26]We can re-examine seller negative feedback and seller warning with seller fixed effects as well, but seller warnings have few within-seller variations by definition (Eachnet blocks a user's access if he/she has more than three Eachnet warnings), and seller negative feedback is a rare event thus not many within-seller variations either.

more driven by cross-seller variations. One explanation is that buyers use seller reputation to distinguish across sellers, but seller behavior upon completion could change with platform policy within a seller. As a seller accumulates seller score, he tends to be more trustworthy, which also explains why buyers are willing to pay more to sellers with higher scores.

6 Conclusion

For e-commerce to fully harvest its advantage in search cost reduction, online platforms must find effective ways to overcome the information problems exacerbated by anonymous trade on the Internet. In this paper, we demonstrate that under certain conditions, buyer protection – one of the most commonly-used tools for trust promotion – may lead to less equilibrium trust and smaller market size. At least in the early age of Eachnet.com, empirical evidence suggests that buyer protection did have a detrimental effect on trust-building and market expansion. Our results imply that healthy e-commerce development requires more than promising protection to buyers. Building institutions, especially a well functioning legal or market system that penalizes cheating sellers, is fundamental to ensure seller trustworthiness.

If buyer protection alone does not boost trust, can buyer protection help build trust if it is used in combination with greater penalties on cheating sellers? One example along this line is the lemon law: a seller of a low quality product is required to reimburse the buyer under the lemon law, which implies that the seller who fails to deliver a high quality product faces a penalty equal to the transaction price, while the buyer enjoys full protection. When the legal cost of enforcing the law is small relative to product value (e.g., for automobiles), this law can be effective in restoring trust in the marketplace. Eachnet's buyer protection program is different from the lemon law because it is the market platform, not the seller, that reimburses the buyer. At first glance, platform reimbursement may ensure fast reimbursement and therefore encourage buyers to trust the market. However, our analysis shows that it may not work well in trust building because it does not punish cheating sellers directly. In fact, under certain conditions, it could attract strategic sellers to take advantage of buyer protection, which eventually hurts trust and market development. How to design an optimal combination of buyer protection and cheating penalty by incorporating enforcement costs deserves future research.

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7 Appendix A: Solution to the Main Model

We solve the model by backward induction. In stage 3, a strategic seller will cheat if $c \geq n = \tau A$ and $n < p$. With sufficient high expected penalty ($n \geq C$), all strategic sellers will not cheat; we assume $n < C$ to avoid this trivial case. For the same reason, we focus on the equilibrium in which $p > n$.[27] When $n < C$, the proportion of cheating among strategic sellers is $1 - \frac{n}{C}$.

Let γ be buyer's rational belief on the probability that the seller she is matched with will deliver a high quality product. A rational buyer will buy the product if $p \leq \gamma v + (1-\gamma)\tau I$, or $v \geq \bar{v} = \frac{p-(1-\gamma)\tau w p}{\gamma}$. This occurs with probability of $0 \leq \frac{V+e-\bar{v}}{2e} \leq 1$. It is clear that conditional on p and the rational expectation of trustworthiness (γ), buyer's willingness to trade increases with the mean valuation of high-quality valuation (V) and the degree of insurance w.

In stage 2, honest sellers will set the price to maximize expected profit. To pool with honest sellers, strategic sellers must set the same price.

Setting a price p will generate for an honest seller the expected profit:

$$\pi^H = (p - c_H)[\frac{V + e - \bar{v}}{2e}]$$

The optimal price has an inner solution when $V - 3e < c_H < V + e$:

$$p(\gamma, V, e, \tau, w, c_H) = \frac{c_H}{2} + \frac{\gamma(V+e)}{2(1-(1-\gamma)\tau w)}$$

If we define the completion rate as $CR \equiv \frac{V+e-\bar{v}}{2e}$, then the corner solution occurs when $CR = 1$ or $CR = 0$, i.e.

$$p(\gamma, V, e, \tau, w) = \begin{cases} \frac{\gamma(V-e)}{1-(1-\gamma)\tau w}, & if\ CR = 1 \\ \frac{\gamma(V+e)}{1-(1-\gamma)\tau w}, & if\ CR = 0 \end{cases}$$

For all solutions, it is easy to see that $\frac{\partial p}{\partial V} > 0$, $\frac{\partial p}{\partial \gamma} > 0$, $\frac{\partial p}{\partial \tau} > 0$, and $\frac{\partial p}{\partial w} > 0$. In what follows, we mainly focus on the more interesting case–inner solution, and turn to the other case when it is necessary. At the optimal price, the probability of sale is $CR = \frac{V+e-\bar{v}}{2e} = \frac{V+e}{4e} - \frac{c_H(1-(1-\gamma)\tau w)}{4e\gamma}$ and the expected profit of an honest seller is $\pi^H = (p - c_H)CR$.

Now we turn to strategic sellers. Given p, if $p \geq C > n$ or $C > p \geq n$, a strategic seller will provide a high quality product if $c < n$, and poor quality otherwise. Thus, before knowing his production cost c, the expected profit for a strategic seller is:

$$\pi^S = E_c\{[(p-c)\frac{n}{C} + (p-n)(1-\frac{n}{C})][\frac{V+e-\bar{v}}{2e}]\} = (p - n + \frac{n^2}{2C})CR$$

[27] As discussed in Section 3, in the extension of the model in which the expected penalty of a strategic seller is uniformly distributed on $[n_1, n_2]$, the equilibrium we focus on is such that $n_1 < p < n_2$.

If $C > n \geq p$, a strategic seller will not provide low quality because the expected penalty n is greater than the price; he will provide high quality as long as his production cost c is below p. Thus, before knowing c, his expected profit will be

$$\pi^{SH} = E_c\{(p-c)[\frac{V+e-\bar{v}}{2e}]\} = \frac{p * CR}{2}$$

and the strategic seller will not enter unless $\pi^{SH} \geq k$. In other words, when $C > n \geq p$, all the strategic traders who choose to enter the market provide high quality products. Consistently, buyers hold the belief of $\gamma = 1$ which leads to $p = (V + e + c_H)/2$. This case is less interesting, so we rule it out by assuming $V + e + c_H > 2n$.

In stage 1, a seller makes his entry decision by comparing the expected profit π^S(or π^H) and his entry cost k. Strategic sellers will enter the market with probability $\rho = \frac{\pi^S}{K}$. The entry probability of honest sellers is $\phi = \frac{\pi^H}{K}$. To ensure $\rho \leq 1$ and $\phi \leq 1$, we assume that $K \geq \frac{(V+e)^2}{8e}$. Accordingly, rational buyers should believe that the probability of getting a high quality product is $\gamma = \frac{\alpha\phi+(1-\alpha)\rho\frac{n}{C}}{\alpha\phi+(1-\alpha)\rho}$. Rearranging terms, we get

$$\frac{1}{1-\gamma} = \frac{\alpha(n-\frac{n^2}{2C}-c_H)}{(1-\alpha)(1-\frac{n}{C})(p-n+\frac{n^2}{2C})} + \frac{1}{(1-\alpha)(1-\frac{n}{C})}$$

We assume $c_H < n - \frac{n^2}{2C}$, i.e., the cost of producing a high quality product(c_H) is lower for an honest seller than a strategic seller¡¯s expected cost. If this assumption holds [28] , then γ is decreasing in p. Thus equations (1) and (2) jointly define p and γ. These two curves determine a unique equilibrium because at $\gamma = 1$, the endpoint of curve (1) at $p = (V + e + c_H)/2$ is greater than the endpoint of curve (2) at $p = n - \frac{n^2}{2C}$ by our assumption $V + e + c_H > 2n$.

The comparative statics results of Propositions 1 and 3 follow easily from examining shifts in the two curves.

Proof of Proposition 2:

we aim to prove $\frac{\partial^2\gamma}{\partial V\partial w} > 0$. We first define the relative ratio of honest seller to strategic seller: $R = \frac{\alpha(p-c_H)}{(1-\alpha)[p-n-\frac{n^2}{2C}]}$. It can be easily shown that R is decreasing with p and increasing with n. Then the buyers' belief curve (2) can be written as a function of R:

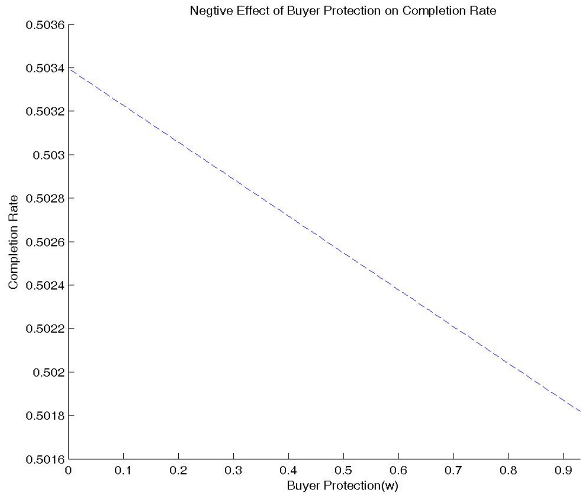
$$\gamma = \frac{\alpha\phi+(1-\alpha)\rho\frac{n}{C}}{\alpha\phi+(1-\alpha)\rho} = 1 - \frac{1-\frac{n}{C}}{1+R} \qquad (11)$$

From the above equation, we may get $\frac{\partial\gamma}{\partial V} = (1-\frac{n}{C})\frac{1}{(1+R)^2}\frac{\partial R}{\partial p}\frac{\partial p}{\partial V}$. Then,

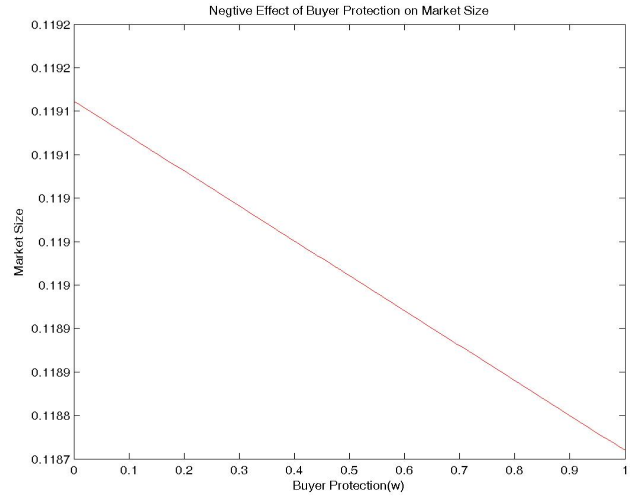
$$\frac{\partial^2\gamma}{\partial V\partial w} = (1-\frac{n}{C})\{\frac{-2}{(1+R)^3}(\frac{\partial R}{\partial p})^2\frac{\partial p}{\partial V} + \frac{-2}{(1+R)^2}\frac{\alpha}{(1-\alpha)}\frac{(n-c_0-\frac{n^2}{2C})}{[p-n-\frac{n^2}{2C}]^3}\frac{\partial p}{\partial w}\frac{\partial p}{\partial V} + \frac{1}{(1+R)^2}\frac{\partial R}{\partial p}\frac{\partial^2 p}{\partial V\partial w}\}$$

Given $\frac{\partial R}{\partial p} < 0$, $\frac{\partial p}{\partial V} > 0$, $\frac{\partial p}{\partial w} > 0$ and $\frac{\partial^2 p}{\partial V\partial w} > 0$, then we could get $\frac{\partial^2\gamma}{\partial V\partial w} > 0$

[28]This assumption is very easy to hold, for example, when the range of the cost distribution(C) is large.



FigureA2(a)



FigureA2(b)

Simulation of Proposition 5:

Simulation results help us find some possible parameters [29] with which buyer protection(w) may negatively affect completion rate as well as market size. Figure A2 confirms our arguments.

8 Appendix B: Two Model Extensions

This appendix presents two model extensions: one allows the platform to limit buyer protection reimbursement to the penalty gathered from cheaters (A); the other allows buyer reporting rate (τ) to increase with the coverage rate of buyer protection (w), which effectively increases the expected penalty ($n = \tau \cdot A$).

In the first case, buyer reimbursement I is set equal to A instead of wp. Under this assumption, a rational buyer will buy the product if $\gamma v + (1-\gamma)\tau I - p \geq 0$, which occurs with probability of $\frac{V+e-\frac{p-(1-\gamma)\tau I}{\gamma}}{2e}$. Thus, an honest seller's expected profit by setting a price $p \geq c_H$ is $\pi^H = (p - c_H)[\frac{V+e-\frac{p-(1-\gamma)\tau I}{\gamma}}{2e}]$.

For an inner solution, the optimal price is given by [30]

$$p(\gamma, V, e, \tau, I, c_H) = \frac{c_H + \tau I}{2} + \frac{(V + e - \tau I)\gamma}{2}. \tag{12}$$

As shown in Figure A1, Equation (12) redefines the price curve: p is now linear and

[29] We set up parameters as follows: $\alpha = 0.75, V = 2, e = 1.6, c_H = 0.4, \tau = 0.5, C = 6, K = 5, A = 8$.

[30] The corner solutions are $p(\gamma, V, e, \tau, I) = \begin{cases} (V+e)\gamma + (1-\gamma)\tau I & \text{if CR} = 0 \\ (V-e)\gamma + (1-\gamma)\tau I & \text{if CR} = 1. \end{cases}$

increases with γ.[31] The belief curve of Equation (2) remains the same. As buyer protection $I(=A)$ increases, curve (12) moves to (12') and curve (2) moves to (2'), so the effect on price is positive and the effect on trustworthiness is ambiguous. In other words, if the platform adopts both buyer protection and cheating penalty such that the two policies balance in budget, their opposite effects on trust (as predicted in Proposition 1) do not necessarily cancel out. This is also consistent with Proposition 2 which predicts that the two policies could be substitutes or complements in terms of their marginal effects on trust.

In the second extension, the buyer reporting rate (τ) is assumed to increase with the coverage rate of buyer protection (w) because reimbursement is conditional on reporting cheating to Eachnet. In that case, the price function can be written as

$$p(\gamma, V, e, \tau, w) = \frac{c_H}{2} + \frac{\gamma(V+e)}{2[1-(1-\gamma)\tau(w)w]}.$$

The only difference from Equation (2) is that $\tau(w)$ is affected by w. Thus, when w goes up, the price curve and the belief curve will both move up. Consequently, the new equilibrium price will be higher and the effect on equilibrium trust is ambiguous. However, as long as $\tau(w)$ does not increase very rapidly in w, our results in the basic model should still hold. Empirically, we do not observe buyer reporting rates separately from the reported seller behavior, but a potential change of the buyer reporting rate in response to buyer protection could affect the interpretation of our results.

[31] According to Equation (12), p increases with γ if $V + e > \tau I = \tau A = n$. This condition is automatically satisfied given the previous assumption of $V + e > 2n - c_H > 2n - (n - \frac{n^2}{2C}) > n$.

Figure 1: Fraction of Transaction Price Subject to Buyer Protection, by Regime

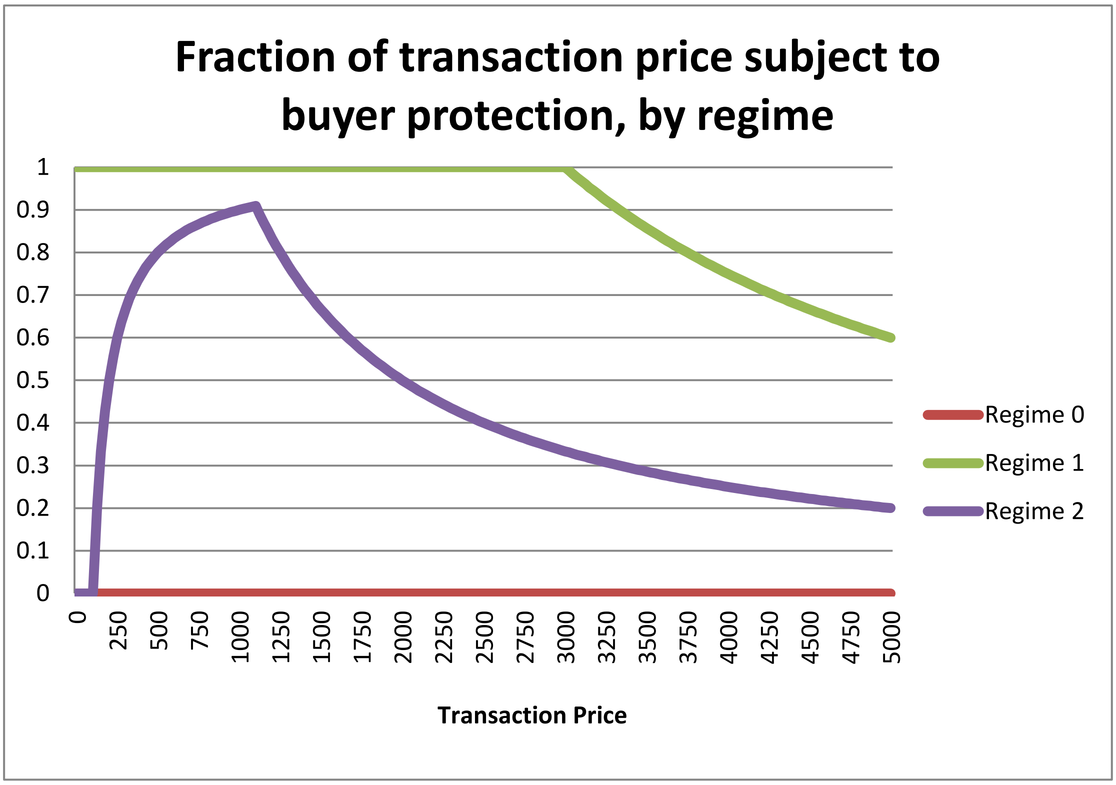


Figure 2: Equilibrium and Comparative Statics: Baseline Model

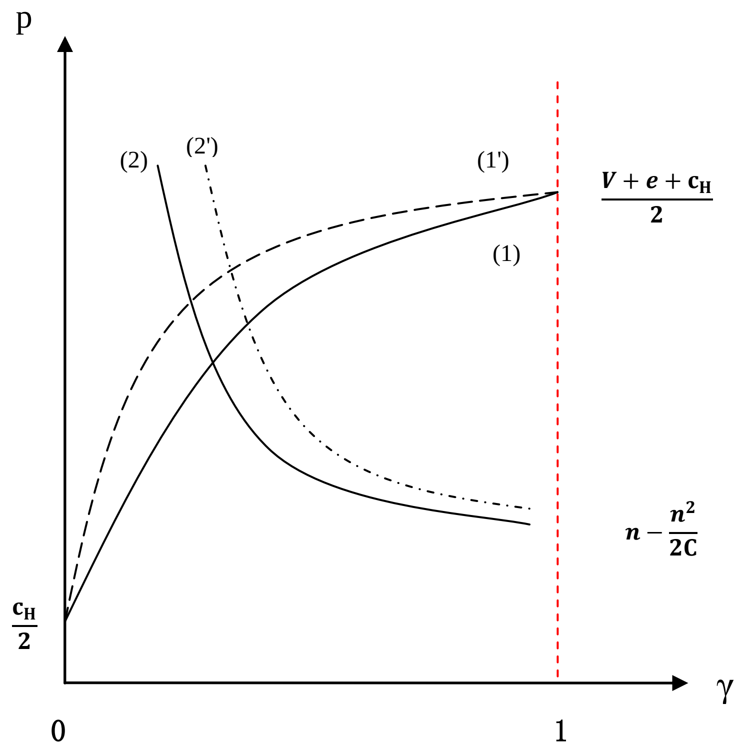


Figure 3: Comparative Statics for the Mean of Buyer Valuation (V)

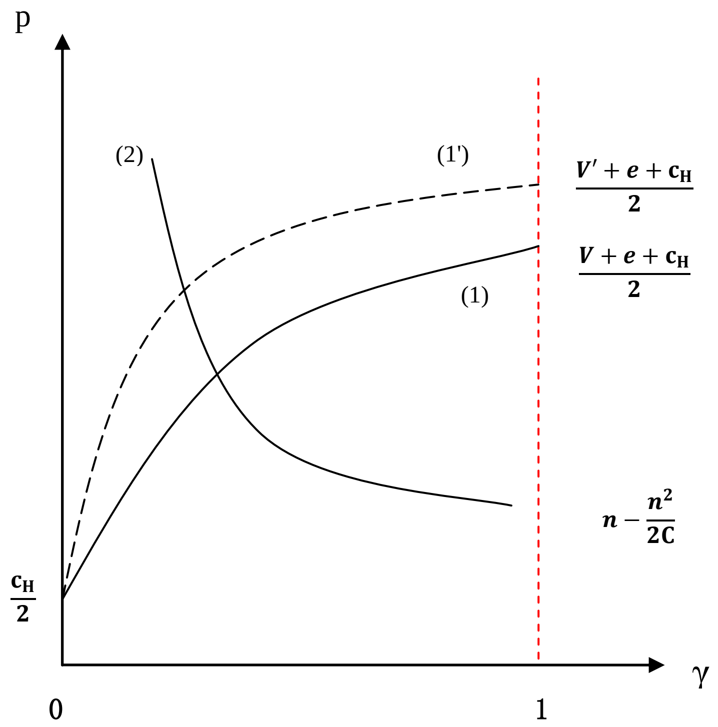
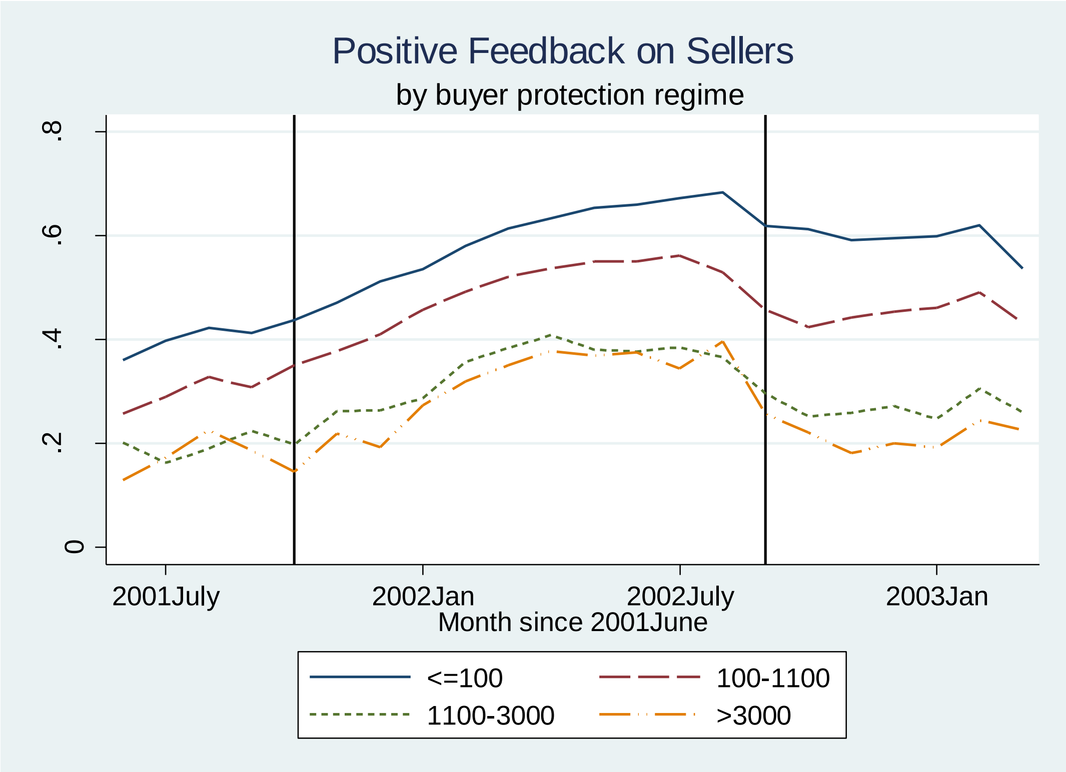
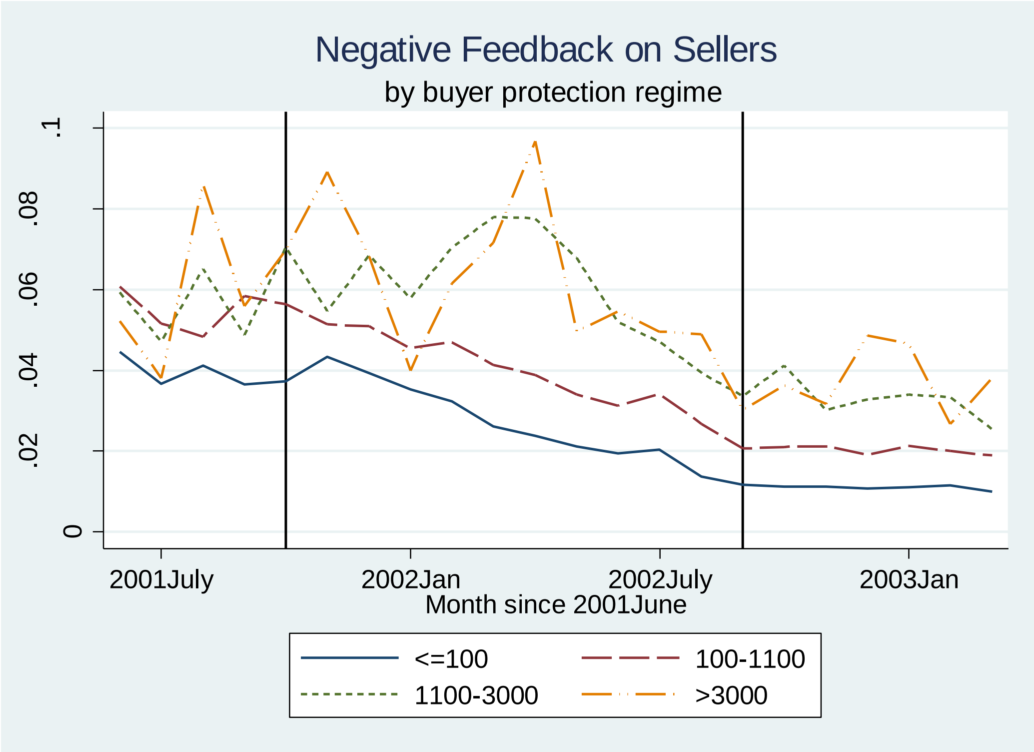


Figure 4: Seller Positive Feedback by Buyer Protection Regime



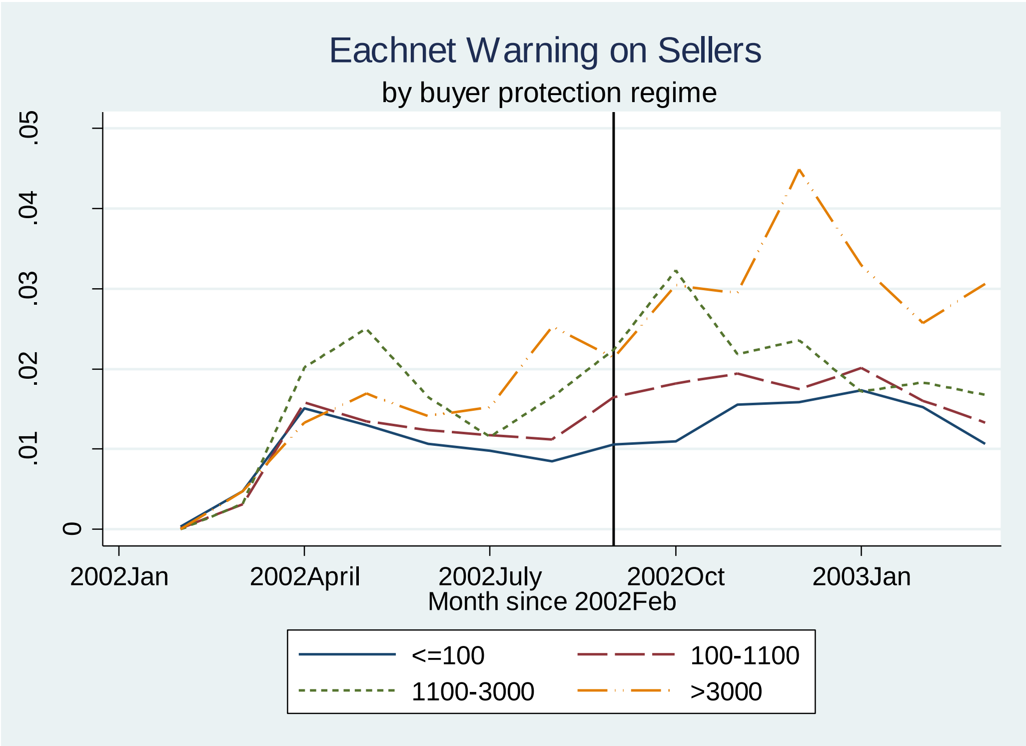
Note: The two vertical lines correspond to the first month of Regime 1 (October 2001) and the first month of Regime 2 (September 2002).

Figure 5: Seller Negative Feedback by Buyer Protection Regime



Note: The two vertical lines correspond to the first month of Regime 1 (October 2001) and the first month of Regime 2 (September 2002).

Figure 6: Seller Warning by Buyer Protection Regime



Note: The vertical line corresponds to the first month of Regime 2 (September 2002).

Table 1: Percentage of the Price Covered by Buyer Protection

Transaction Price (RMB)	Regime 0 05/2001-09/2001	Regime 1 10/2001-08/2002	Regime 2 09/2002-03/2003
(0,100]	0%	100%	0%
(100,1100]	0%	100%	$\frac{p-100}{p}$
(1100,3000]	0%	100%	$\frac{\min(p-100,1000)}{p}$
above 3000	0%	$\frac{3000}{p}$	$\frac{1000}{p}$

Table 2: Summary Statistics

	Regime 0 6/01-9/01 mean(median)	Regime 1 10/01-8/02 mean(median)	Regime 2 9/02-3/03 mean(median)
# of calendar months	4	11	7
# of records	78116	574804	917414
# of unique listings	76253	490153	725496
# of unique listings per month	19063	44559	103642
# of unique sellers	11259	38432	47558
Summary per unique listing			
% with fixed p	51.48%	74.01%	85.67%
fixed p | have fixed p	951.52 (150)	581.32 (128)	404.70 (100)
% with reservation price	49.56%	36.80%	25.61%
reservation price | have reservation p	1143.78 (250)	791.70 (185)	661.84 (180)
% allow auction	100%	95.56%	88.93%
starting price of auction | allow auction	756.28 (100)	335.27(68)	243.47 (50)
% have picture	39.99%	77.70%	86.31%
% have bold font	35.28%	12.46%	10.54%
condition of item - new1	0.00%	0.00%	0.00%
condition of item - new2	60.44%	76.46%	82.82%
condition of item - new3	31.34%	18.93%	13.32%
condition of item - new4	5.45%	2.60%	1.78%
condition of item - new5	2.56%	1.82%	1.88%
condition of item - new6	0.22%	0.18%	0.20%
# of items listed in the same listing	1.89	3.29	2.67
with>=2 items listed in the same listing?	7.19%	21.95%	30.83%
With >=100 items listed in the same listing?	0.49%	1.69%	0.66%
seller age(days since registration)	111.40	218.82	274.88
# of completed listings by t	35.43	159.15	243.67
% seller score missing	58.98%	27.45%	25.48%
% seller score = 0	2.68%	1.24%	0.33%
% seller score < 0	4.07%	0.98%	0.19%
seller score | have score	7.94	72.15	125.62
seller score is fishy (i.e. missing, negative or zero)	65.73%	29.66%	26.00%
Seller's last listing is more than 1 month ago	13.63%	5.31%	4.20%
Competition per 1000 view count	19.78	5.18	4.18
=1 if Competition>=50	10.08%	0.32%	0.12%
% of listings with at least one completion	35.44%	55.22%	54.42%

Table 2 Continued: Summary Statistics

	Regime 0 6/01-9/01 mean(median)	Regime 1 10/01-8/02 mean(median)	Regime 2 9/02-3/03 mean(median)
Conditional on completion, summary per transaction			
# of completed transactions	27363	355317	586659
% completion by auction	62.03%	47.94%	38.12%
final price	673.33 (150)	424.35 (90)	270.77 (60)
% of final price protected by Eachnet	0%	99.04%	19.58%
buyer age(days since registration)|completion	85.57	155.95	170.66
% with any seller feedback	45.08%	64.85%	57.35%
% seller receiving positive feedback	32.68%	56.95%	53.32%
% seller receiving negative feedback	4.84%	3.13%	1.51%
% with seller warning(after 2/02 only)		0.88%	1.53%
same region	59.73%	44.66%	35.43%

Note: Competition is defined as the number of listings (in the most detailed product category) in the past 7 days per 1000 view count.

Table 3: The Effect of Buyer Protection on Seller Positive Feedback (conditional on completed listings, linear probability model)

	Dependent Variable = 1 if Seller Receives Positive Feedback								
Price used to calculate buyer protection	Final Price			Buy-it-now Price			Predicted Price		
% price protected by Eachnet	-0.086**		-0.087**	-0.082**		-0.084**	-0.044**		-0.047**
	(0.003)		(0.003)	(0.003)		(0.003)	(0.004)		(0.004)
% of protection | p<=500		-0.075**			-0.039**			-0.042**	
		(0.003)			(0.004)			(0.004)	
% of protection | p>500		-0.115**			-0.093**			-0.066**	
		(0.003)			(0.005)			(0.005)	
price (in thousand)	-0.030**	-0.027**	-0.030**	-0.031**	-0.023**	-0.031**	-0.063**	-0.056**	-0.062**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
quadratic price	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.004**	0.003**	0.004**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log (seller score at time of listing)	-0.005**	-0.006**	0.030**	-0.006**	-0.006**	0.032**	-0.006**	-0.006**	0.034**
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)
=1 if seller score is missing or <=0	-0.080**	-0.079**	-0.066**	-0.074**	-0.080**	-0.068**	-0.080**	-0.080**	-0.060**
	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.010)	(0.003)	(0.003)	(0.010)
after protection * log(seller score)			-0.023**			-0.027**			-0.023**
			(0.003)			(0.004)			(0.005)
after protection * seller score missing or <=0			-0.028**			-0.023+			-0.027*
			(0.009)			(0.013)			(0.013)
after warning * log(seller score)			-0.012**			-0.010**			-0.017**
			(0.002)			(0.002)			(0.002)
after warning * seller score missing or <=0			0.022**			0.025**			0.013
			(0.007)			(0.009)			(0.009)
Observations	969,337	969,337	969,337	789,908	783,566	789,908	783,566	783,566	783,566
R-squared	0.161	0.161	0.161	0.160	0.161	0.160	0.161	0.161	0.161

Note: Predicted price refers to the average price of similar items (in the same four-level category code) in the last seven days before this listing. All regressions control for year-month fixed effects, day of week fixed effects, two-level product category fixed effects, competition as measured by the # of similar listings in the last 7 days per thousand view count, a dummy if the competition index is over 50, seller's Eachnet age, buyer's Eachnet age, log buyer score, a dummy of buyer score being negative, zero or missing, buyer region fixed effects, seller region fixed effects, seller gender, buyer gender, and listing attributes. Robust standard errors in parentheses are clustered at the listing id level, +p<10%,*p<5%,**p<1%.

Table 4: The Effect of Buyer Protection on Seller Negative Feedback and Warning (conditional on completed listings, linear probability model)

	Seller Receives Negative Feedback						Seller Receives Eachnet Warning		
Price used to calculate buyer protection	Final price		Buy-it-now price		Predicted price		Final price	Buy-it-now price	Predicted price
% price protected by Eachnet	0.003**	0.003**	0.004**	0.004**	-0.008**	-0.007**	0.003**	0.006**	0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
price (in thousand)	0.002**	0.002**	0.004**	0.004**	0.006**	0.006**	-0.000	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
quadratic price	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	0.000+	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log (seller score at time of listing)	-0.003**	-0.007**	-0.002**	-0.005**	-0.003**	-0.008**	-0.002**	-0.002**	-0.002**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
=1 if seller score is missing or <=0	0.011**	0.007*	0.010**	0.012*	0.011**	0.003	0.011**	0.010**	0.012**
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
after protection * log(seller score)		0.000		-0.001		0.001			
		(0.001)		(0.002)		(0.002)			
after protection * seller score missing or <=0		0.008+		0.004		0.014*			
		(0.005)		(0.006)		(0.007)			
after warning * log(seller score)		0.005**		0.004**		0.004**			
		(0.001)		(0.001)		(0.001)			
after warning * seller score missing or <=0		-0.006+		-0.007		-0.008+			
		(0.003)		(0.004)		(0.005)			
Observations	969,337	969,337	789,908	789,908	783,566	783,566	890,288	741,868	739,398
R-squared	0.015	0.015	0.014	0.014	0.015	0.015	0.011	0.010	0.011

Note: Predicted price refers to the average price of similar items (in the same four-level category code) in the last seven days before this listing. All regressions control for year-month fixed effects, day of week fixed effects, two-level product category fixed effects, competition as measured by the # of similar listings in the last 7 days per thousand view count, a dummy if the competition index is over 50, seller's Eachnet age, buyer's Eachnet age, log buyer score, a dummy of buyer score being negative, zero or missing, buyer region fixed effects, seller region fixed effects, seller gender, buyer gender, and listing attributes. Robust standard errors in parentheses are clustered at the listing id level, +p<10%,*p<5%,**p<1%.

Table 5: Robustness Check

	Seller Receives Positive Feedbacks			
	Linear p	cubic p	trend*price	cubic p
% price protected by Eachnet	-0.050**	-0.040**	-0.048**	-0.040**
	(0.003)	(0.004)	(0.004)	(0.004)
predicted price (in thousand)	-0.040**	-0.098**	-0.035**	-0.097**
	(0.001)	(0.005)	(0.003)	(0.005)
quadratic price		0.013**		0.013**
		(0.001)		(0.001)
cubic price		-0.000**		-0.000**
		(0.000)		(0.000)
trend*price			-0.000+	-0.000
			(0.000)	(0.000)
log (seller score at time of listing)	0.034**	0.034**	0.035**	0.034**
	(0.004)	(0.004)	(0.004)	(0.004)
=1 if seller score is missing or <=0	-0.062**	-0.058**	-0.063**	-0.058**
	(0.010)	(0.010)	(0.010)	(0.010)
after protection * log(seller score)	-0.023**	-0.023**	-0.024**	-0.023**
	(0.004)	(0.005)	(0.005)	(0.005)
after protection * seller score missing or <=0	-0.026*	-0.029*	-0.025+	-0.029*
	(0.013)	(0.013)	(0.013)	(0.013)
after warning * log(seller score)	-0.017**	-0.017**	-0.017**	-0.017**
	(0.002)	(0.002)	(0.002)	(0.002)
after warning * seller score missing or <=0	0.013	0.014	0.014	0.014
	(0.008)	(0.009)	(0.009)	(0.009)
Observations	783,566	783,566	783,566	783,566
R-squared	0.161	0.161	0.161	0.161

Note: Predicted price refers to the average price of similar items (in the same four-level category code) in the last seven days before this listing. All regressions control for year-month fixed effects, day of week fixed effects, two-level product category fixed effects, competition as measured by the # of similar listings in the last 7 days per thousand view count, a dummy if the competition index is over 50, seller's Eachnet age, buyer's Eachnet age, log buyer score, a dummy of buyer score being negative, zero or missing, buyer region fixed effects, seller region fixed effects, seller gender, buyer gender, and listing attributes. Robust standard errors in parentheses are clustered at the listing id level, +p<10%,*p<5%,**p<1%.

Table 6: The Effect of Buyer Protection on Completion Rate and Price

	Completed		log (final price)	
% predicted price protected by Eachnet	-0.009**	-0.007**	0.560**	0.573**
	(0.002)	(0.002)	(0.026)	(0.026)
predicted price (in thousand)	-0.005**	-0.005**		
	(0.001)	(0.001)		
log (seller score at time of listing)	0.019**	0.046**	0.075**	-0.131**
	(0.000)	(0.003)	(0.003)	(0.017)
=1 if seller score is missing or <=0	-0.422**	-0.195**	0.304**	-0.088+
	(0.001)	(0.008)	(0.018)	(0.049)
after protection * log(seller score)		-0.013**		0.096**
		(0.004)		(0.018)
after protection * seller score missing or <=0		-0.084**		0.301**
		(0.010)		(0.057)
after warning * log(seller score)		-0.017**		0.114**
		(0.002)		(0.007)
after warning * seller score missing or <=0		-0.167**		0.089*
		(0.006)		(0.036)
Observations	985,265	985,265	783,566	783,566
R-squared	0.280	0.282	0.440	0.440

Note: A listing is defined completed if the listing leads to at least one completed transaction. Predicted price refers to the average final price of similar items (in the same level-four category) completed in the last seven days before the study listing. All regressions control for year-month fixed effects, day of week fixed effects, product category fixed effects, seller's Eachnet age, seller region fixed effects, seller gender, listing attributes, predicted price, competition measured by # of similar listings in last 7 days per thousand view count, and a dummy if the competition index is over 50. Robust standard errors in parentheses are clustered at the listing id level, +p<10%,*p<5%,**p<1%.

Table 7: The Effect of Buyer Protection on Market Size

	log (total # of listings)	log (total # of listed items)	log (total # of unique sellers)
	(1)	(2)	(3)
Panel A: Conditional on 116 categories that existed at the start of sample (June 2001)			
% protected (calculated by $\bar{p}_{k0}$)	-0.726**	-0.792**	-0.649**
	(0.181)	(0.219)	(0.174)
Observations	2,419	2,419	2,399
R-squared	0.886	0.819	0.858
Panel B: Full Sample			
% protected (calculated by $\bar{p}_{k0}$)	-0.647**	-0.823**	-0.572**
	(0.175)	(0.217)	(0.166)
Observations	2,797	2,797	2,753
R-squared	0.889	0.821	0.854

Note: $\bar{p}_{k0}$ stands for the average transaction price of category k in the first month that k appeared in our analysis sample. All regressions control for product category fixed effects, year-month fixed effects, After warning*$\bar{p}_{k0}$. Robust standard errors in parentheses are clustered by two-level product category, ** p<0.01, * p<0.05, + p<0.1.

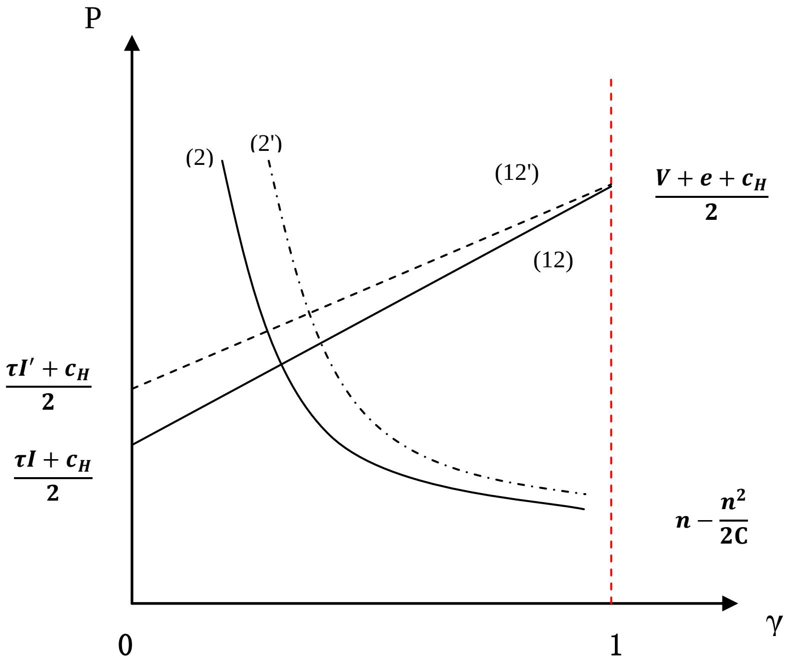
Table 8: Results with Seller Fixed Effects (Linear Probability Model)

Dependent Variable	Seller Positive Feedback		Completed		log (final price)	
% predicted price protected by Eachnet	-0.039**	-0.040**	-0.010**	-0.010**	0.546**	0.548**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.022)	(0.022)
predicted price (in thousand)	-0.040**	-0.039**	-0.001	-0.001		
	(0.003)	(0.003)	(0.001)	(0.001)		
quadratic price	0.002**	0.002**				
	(0.000)	(0.000)				
log (seller score at time of listing)	0.056**	0.056**	0.001*	0.004	0.093**	-0.023
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.015)
=1 if seller score is missing or <=0	-0.157**	-0.157**	-0.164**	-0.113**	0.114**	-0.132**
	(0.001)	(0.001)	(0.003)	(0.009)	(0.014)	(0.046)
after protection * log(seller score)		-0.009+		0.007+		0.047**
		(0.005)		(0.004)		(0.015)
after protection * seller score missing or <=0		-0.003		-0.011		0.184**
		(0.016)		(0.011)		(0.053)
after warning * log(seller score)		-0.025**		-0.011**		0.073**
		(0.002)		(0.002)		(0.007)
after warning * seller score missing or <=0		0.021+		-0.049**		0.060+
		(0.011)		(0.007)		(0.032)
Observations	792,263	792,263	985,265	985,265	783,566	783,566
R-squared	0.271	0.271	0.548	0.548	0.657	0.657

Note: A listing is defined completed if the listing leads to at least one completed transaction. Predicted price refers to the average price of similar items (in the same four-level category code) in the last seven days before this listing. All regressions control for seller fixed effects, year-month fixed effects, day of week fixed effects, two-level product category fixed effects, competition as measured by the # of similar listings in the last 7 days per thousand view count, a dummy if the competition index is over 50, seller's Eachnet age,and listing attributes. Feedback and completion regressions control for price interacted with linear time trend. Feedback regressions control for buyer's Eachnet age, log buyer score, a dummy of buyer score being negative, zero or missing, buyer region fixed effects, and buyer gender. In feedback and price regressions, errors are clustered by unique listing id. Robust standard errors in parentheses, +p<10%,*p<5%,**p<1%.

Appendix Figure

Figure A1: Model Extension



Appendix Table 1: Summary Statistics (conditional on predicted price is not missing)

	Regime 0 6/01-9/01 mean(median)	Regime 1 10/01-8/02 mean(median)	Regime 2 9/02-3/03 mean(median)
# of calendar months	4	11	7
# of records	31523	429561	762907
# of unique listings	30759	361152	593354
# of unique listings per month	4394	32832	84765
# of unique sellers	5905	31142	42286
Summary per unique listing			
% with fixed p	51.37%	75.51%	86.04%
fixed p | have fixed p	1104.35 (220)	561.58 (130)	363.97 (100)
% with reservation price	49.92%	37.02%	25.46%
reservation price | have reservation p	1278.77 (360)	765.28 (200)	593.91 (180)
% allow auction	100%	95.89%	88.92%
starting price of auction | allow auction	822.02 (100)	303.49 (68)	212.61 (53)
% have picture	41.37%	79.41%	86.62%
% have bold font	39.06%	12.76%	10.66%
condition of item - new1	0.00%	0.00%	0.00%
condition of item - new2	55.03%	77.08%	83.48%
condition of item - new3	36.32%	18.93%	13.10%
condition of item - new4	6.35%	2.51%	1.65%
condition of item - new5	2.13%	1.30%	1.59%
condition of item - new6	0.18%	0.17%	0.19%
# of items listed in the same listing	1.56	3.02	2.67
with>=2 items listed in the same listing?	5.47%	22.39%	32.07%
With >=100 items listed in the same listing?	0.24%	1.43%	0.62%
seller age(days since registration)	115.36	223.67	273.49
# of completed listings by t	49.76	179.25	259.14
% seller score missing	49.29%	24.97%	24.51%
% seller score = 0	3.22%	1.13%	0.32%
% seller score < 0	6.13%	0.91%	0.20%
seller score | have score	9.63	78.23	131.10
seller score is fishy (i.e. missing, negative or zero)	58.64%	27.01%	25.04%
Seller's last listing is more than 1 month ago	12.14%	4.77%	4.03%
Competition per 1000 view count	12.69	4.36	3.77
=1 if Competition>=50	4.11%	0.15%	0.00%
% of listings with at least one completion	39.14%	56.95%	55.14%

Appendix Table 1 continued: Summary Statistics (conditional on predicted price is not missing)

	Regime 0 6/01-9/01 mean(median)	Regime 1 10/01-8/02 mean(median)	Regime 2 9/02-3/03 mean(median)
Conditional on completion, summary per transaction			
# of completed transactions	12802	274099	496665
% completion by auction	60.90%	47.15%	37.53%
final price	806.65 (200)	431.18 (96)	251.89 (63)
% of final price protected by Eachnet	0%	99.02%	19.90%
buyer age(days since registration)|completion	88.52	155.95	169.24
% with any seller feedback	44.91%	64.96%	57.01%
% seller receiving positive feedback	33.33%	57.20%	52.90%
% seller receiving negative feedback	5.07%	3.10%	1.53%
% with seller warning(after 2/02 only)		0.89%	1.54%
same region	57.89%	43.76%	35.11%

Note: Competition is defined as the number of listings (in the most detailed product category) in the past 7 days per 1000 view count.

Appendix Table 2: Pretreatment Trend Test for Feedback Regression

2001/6-2001/9	Seller Receives Positive Feedback			Seller Receives Negative Feedback		
Price used to calculate buyer protection	Final price	Buy-it-now price	Predicted price	Final price	Buy-it-now price	Predicted price
2001/7 * Fully covered(0<price<=100)	0.029	0.005		0.007	0.007	
	(0.020)	(0.019)		(0.011)	(0.008)	
2001/7 * % covered(100<price<=1100)	0.037+	0.023	-0.021	0.010	0.006	-0.010
	(0.019)	(0.018)	(0.027)	(0.012)	(0.009)	(0.011)
2001/7 * % covered(price>=1100)		0.007	-0.003		-0.009	-0.009
		(0.025)	(0.024)		(0.017)	(0.008)
2001/8 * Fully covered(0<price<=100)		-0.009			0.000	
		(0.022)			(0.009)	
2001/8 * % covered(100<price<=1100)	0.027	0.004	0.037	-0.005	0.003	-0.005
	(0.017)	(0.019)	(0.030)	(0.008)	(0.010)	(0.012)
2001/8 * % covered(price>=1100)	-0.012	0.015	-0.006	0.015	-0.005	-0.001
	(0.022)	(0.026)	(0.026)	(0.013)	(0.017)	(0.009)
2001/9 * Fully covered(0<price<=100)	-0.008	-0.011		-0.006	0.001	
	(0.017)	(0.021)		(0.008)	(0.009)	
2001/9 * % covered(100<price<=1100)		0.007	0.042		0.014	0.006
		(0.019)	(0.030)		(0.010)	(0.012)
2001/9 * % covered(price>=1100)	0.008	0.051+	0.021	-0.010	-0.015	-0.007
	(0.021)	(0.028)	(0.026)	(0.013)	(0.017)	(0.009)
Observations	27,361	27,361	27,361	27,361	27,361	27,361
R-squared	0.434	0.434	0.433	0.063	0.063	0.063

Note: Predicted price refers to the average price of similar items (in the same four-level category code) in the last seven days before this listing. All regressions control for year-month fixed effects, day of week fixed effects, two-level product category fixed effects, competition as measured by the # of similar listings in the last 7 days per thousand view count, a dummy if the competition index is over 50, seller's Eachnet age, buyer's Eachnet age, log buyer score, a dummy of buyer score being negative, zero or missing, buyer region fixed effects, seller region fixed effects, seller gender, buyer gender, and listing attributes. Robust standard errors in parentheses are clustered at the listing id level, +p<10%,*p<5%,**p<1%.

Appendix Table 3: Pretreatment Trend Test for Market Size Regression

2001/6-2001/9	log (total # of listings)	log (total # of listed items)	log (total # of unique sellers)
2001/7 * Fully covered(0< p<=100)	0.122	-0.024	0.239
	(0.254)	(0.397)	(0.292)
2001/7 * % covered(100<p<=1100)	0.057	0.400	-0.044
	(0.283)	(0.522)	(0.391)
2001/7 * % covered(p>=1100)	0.410	0.380	
	(0.688)	(0.922)	
2001/8 * Fully covered(0<p<=100)			
2001/8 * % covered(100<p<=1100)	-0.071	0.193	
	(0.280)	(0.489)	
2001/8 * % covered(p>=1100)	0.219	0.482	-0.228
	(0.402)	(0.688)	(0.744)
2001/9 * Fully covered(0<p<=100)	-0.059	-0.306	0.178
	(0.220)	(0.398)	(0.313)
2001/9 * % covered(100<p<=1100)			-0.051
			(0.408)
2001/9 * % covered(p>=1100)			-1.021
			(1.157)
Observations	346	346	343
R-squared	0.993	0.987	0.985

Note: we use the average transaction price of category k in the first month that k appeared in our analysis sample. All regressions control for product category fixed effects, year-month fixed effects, After warning*$\overline{p}_{k0}$. Robust standard errors in parentheses are clustered by two-level product category, ** p<0.01, * p<0.05, + p<0.1.