How to Promote Trust: Theory and Evidence from China*

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Abstract

Economists have long recognized the importance of trust, but how can trust be enhanced in a marketplace? We set up a rational expectation model that allows the marketplace to target buyer trusting (via a buyer protection program) and seller trustworthiness (via penalty on cheaters) separately. We show that these two policies have opposite effects on the equilibrium level of trust: buyer protection increases buyer willingness to trade and therefore invites strategic sellers to enter and cheat; in contrast, a penalty on cheating sellers raises the cost of cheating and leads to more honest behavior.

Using transaction-level data from Eachnet.com (an eBay equivalent in China), which introduced different buyer protection policies and a warning system in its early time, we find evidence highly consistent with the theory. More generous buyer protection led to more seller cheating. In particular, sellers that entered the market after the introduction of buyer protection were more likely to cheat and became more trustworthy when the platform adopted the warning system. Reputable sellers were less likely to cheat, but this effect was weakened after the introduction of buyer protection and the warning system. These findings suggest that a trust-promoting policy aimed at buyer trusting may not be effective if it is not accompanied by additional incentives to improve trustworthiness.

JEL: D8, L15, L81.

Keywords: Trust, trusting, trustworthiness, e-commerce, China.

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1 Introduction

Economists have long recognized the importance of trust. Researchers have argued or demonstrated that trust is associated with better economic performance, higher judicial efficiency, less government corruption, and more effective contractual enforcement (Arrow 1972; Greif 1993; Putnam 1993; Fukuyama 1995; Knack and Keefer, 1997; Guiso *et al.*, 2004; Karlan, 2005, Aghion *et al.*, 2010, Algan and Cahuc, 2010, Tabellini, 2010). If trust is so important, a natural question is what can be done to enhance trust. One piece of received wisdom is that the trust level in a society will be higher if individuals, firms, and organizations have built reputations over time. But reputation building requires repeated interactions and other institutional supports (e.g., good monitoring), making it not applicable to all cases. In this paper, we analyze two alternative trust-promoting policies: buyer protection targeting buyer trusting and cheating penalty targeting seller trustworthiness.

Since "trust" does not have a uniform definition in the existing literature, let us first be clear how it is defined in this paper. We define "trusting" as the extent to which a buyer believes 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. Putting it differently, trusting is about demand (buyer willingness to pay), trustworthiness is about supply (seller willingness to deliver high-quality products), and trust is the equilibrium level where demand meets supply (rational expectation). The existing literature often refers to trust as "trusting" and measures it by surveying whether people trust each other and expect cooperative behavior.[1] In comparison, we emphasize the interaction of trusting and trustworthiness and investigate how institutional changes affect the equilibrium level of trust.

We build a simple rational expectation model in which buyers and sellers meet in a marketplace (e.g., an on-line trading platform). 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 the valuation of high-quality products; sellers are heterogeneous in entry cost and production cost of high-quality products (besides their honest

[1] For example, the World Values Survey used in Knack and Keefer (1997) gauges trust by the question "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?" The same attitudinal question is used in the National Opinion Research Center's General Social Survey (GSS).

or strategic types). If a seller delivers a low-quality product, the buyer will report to the platform with a certain probability; upon buyer reporting, the platform will impose some penalty on the guilty seller. In this model, strategic sellers deliver high-quality products only when their production costs are lower than the expected penalty of cheating. Based on the entry behavior of honest and strategic sellers and the cheating choice of strategic sellers, buyers form a rational belief in the equilibrium level of trust. In this framework, the platform considers two policies: offering buyer protection to cover damage from low-quality products or imposing a penalty on cheating sellers.

We show that these two policies have opposite effects on equilibrium trust. For buyer protection, more generous coverage offers buyers better protection against cheating, hence increasing their willingness to buy conditional on price and belief in seller trustworthiness. In response, sellers raise the price, and an expectation of higher profits motivates more sellers to enter. In this process, strategic sellers gain more from the increased trusting level than honest sellers because strategic sellers can profit by delivering a high-quality product or cheating. As a result, higher trusting attracts disproportionately more strategic sellers, reducing the equilibrium level of trust. In contrast, punishment of cheaters makes strategic sellers less likely to cheat. By rational expectation, buyers are more trusting and willing to pay a higher price, but strategic sellers do not gain more than honest sellers because their cheating behavior is constrained by the harsher punishment. In equilibrium, a cheating penalty increases prices as well as the equilibrium level of trust.

We apply our theory to a large transaction data set from Eachnet.com (an eBay equivalent in China). In its early days, Eachnet experimented with multiple tools to boost trust, including buyer protection, seller feedback scores, and a warning system, which offers excellent opportunities for us to identify the effects of these policies on market outcomes. 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. These variations allow us to identify the effect of buyer protection policy from overall market growth. Between the two buyer protection regimes, Eachnet started to issue warnings to traders who were found guilty upon their trading partners' complaints to Eachnet. In addition to damaging seller reputation, warnings could result in a complete ban on trading on Eachnet, effectively the only online trading platform in China at that time. Since we observe seller feedback and the Eachnet warning on the *same* transaction, the data help us infer seller behavior separately from buyer reporting.

After controlling for market growth and other factors, we find that (1) more generous buyer protection leads to more seller cheating, (2) seller cohorts that enter after the introduction of buyer protection are more likely to cheat, but this effect is alleviated by the introduction of the warning system; (3) seller reputation (measured by feedback scores) predicts seller trustworthiness, but the two trust-promoting policies – buyer protection and warning – make seller trustworthiness less sensitive to seller reputation; (4) transaction price increases with the coverage of buyer protection; and (5) buyer protection has differential effects on completion depending on product value, but the overall effect of buyer protection on seller revenue is positive. These findings are highly consistent with the model predictions, suggesting that different trust-building institutions can have different effects on the equilibrium level of trust depending on whether they target trusting or trustworthiness: institutions aiming at improving seller trustworthiness are effective in promoting trust, but institutions aiming at boosting buyer trusting (without simultaneous changes in seller trustworthiness or buyer reporting) in fact reduce trust.

Our paper makes two contributions to the literature on the determinants of trust, see, e.g., La Porta *et al.* (1997), Alesina and La Ferrara (2002), and Algan and Cahuc (2010). First, while the literature defines trust as beliefs or attitudes that are shaped by personal experience, community characteristics, and cultural environment, we consider trust as 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). Second, we build an equilibrium model of trust and present evidence as to how institutions such as buyer protection and cheating penalty enhance trust. In comparison, the existing literature is more concerned with cultural determinants of trust. Through both theoretical analysis and empirical investigation, we show that a simple push on buyer trusting actually leads to more cheating.

Our paper is also related to the growing literature on online reputation.[2] Instead of examining the feedback score system directly, we focus on buyer protection and platform warning while taking the feedback score system as given. This is a significant complement to the literature because both buyer protection and platform monitoring are widely used in e-commerce in addition to feedback scores. To our best knowledge, Roberts (2011) is the only one that has used

[2] See Bajari and Hortascu (2004) and Dellarocus (2003) for literature reviews of the eBay reputation system. E-commerce also motivates experimental studies on reputation building (Bohnet and Huck, 2004) and ways to improve the feedback system (Bolton, Katok and Ockenfels, 2004).

online data to study platform-offered buyer protection program. He finds no evidence for buyer protection to substitute for seller reputation, probably because the market is skeptical about the protection policy. In contrast, we show that the sensitivity of cheating behavior to reputation is weakened by the platform's buyer protection and the warning system. More importantly, we lay out an explicit model to clarify the mechanisms of trust-building policies; we also use transaction-level trade outcomes to directly measure the policies' impact on sellers' cheating behavior. In comparison, Roberts (2011) offers no theory[3] and examines pricing instead of equilibrium cheating behavior.[4] As shown below, buyer protection has opposite effects on price and seller cheating, and different policies have different impacts on equilibrium trust, although their impacts on pricing are similar.

The rest of the paper is organized as follows: Section 2 presents our model, Section 3 describes the background and Eachnet data, Section 4 discusses our econometric specifications and identification, and Section 5 reports results. A conclusion is offered in Section 6.

2 Theory

2.1 The model

Consider a market (a trading platform such as Eachnet) where there are two types of sellers: honest or strategic. Only a seller knows his own type. In the population, the proportion of honest sellers is $\alpha \in (0, 1)$. An honest seller always honors his promise. Honoring one's promise means delivering a high-quality product and cheating means delivering a low-quality product. Producing low-quality costs zero to any seller. The cost of a high-quality product is also zero for an honest seller, so he never cheats.

A strategic seller honors his promise only when it is in his interest. We assume that the cost of a strategic seller producing 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 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

[3] Some of his conjectures about the policy's working mechanisms are confirmed in our theory.

[4] Roberts (2011) examines sales probability as well, as do we.

$n = \tau A$. In our empirical setting, seller penalty A includes an explicit warning from Eachnet (in terms of threat to deny market access) and implicit consequence of receiving one extra negative feedback in the online system (in terms of lower probability and/or lower price to sell in the future). For simplicity, we do not model sellers' dynamic reputation building in feedback scores, but readers can consider loss of reputation as an element of the cheating penalty (A).

A poor quality product has zero value to buyers, but the value of a high quality product v is uniformly distributed on $[V-e, V+e]$ with $V \geq e \geq 0$. We assume that all buyers hold a rational belief about the likelihood of a seller honoring his promise. All buyers and sellers are 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.[5]
- 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. For simplicity, we assume that the critical masses of buyers and sellers are such that one seller is matched with one buyer. The seller in each match announces a price p.[6]
- In stage 3, the buyer in a match decides whether to buy or not. 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 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 and pricing de-

[5]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 main results continue to hold. Proofs are available upon request.

[6]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.

cision in order to maximize his (expected) profit net of penalty; each buyer makes an optimal buy-or-not-buy decision in order to maximize her valuation of the product net of price; and each buyer's belief in the probability of receiving low quality after purchase reflects the actual probability of cheating in the marketplace. The model can be solved by backward induction, and the derivation is contained in the Appendix.

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. The equilibrium level of trust and the equilibrium price are jointly determined by the following two equations:

$$p(\gamma, V, e, \tau, w) = \begin{cases} \frac{0.5\gamma(V+e)}{1-(1-\gamma)\tau w}, & \text{if } \frac{V}{3} \leq e \leq V, \\ \frac{\gamma(V-e)}{1-(1-\gamma)\tau w}, & \text{if } 0 \leq e < \frac{V}{3}. \end{cases} \tag{1}$$

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

Equation (1) is derived from sellers' optimal pricing decision, given buyers' trusting level γ. As shown in Figure 1, Equation (1) depicts p as an increasing function of γ, because the more likely it is that buyers believe sellers will deliver high quality products (higher γ), the more they are willing to pay for the item.[7] This motivates sellers to charge higher prices. On the other hand, the curve corresponding to Equation (2) is downward sloping because, in rational expectation, buyer belief in the probability of getting high quality products depends on the relative ratio of honest and strategic sellers in the market, measured by $R = \frac{\alpha\phi}{(1-\alpha)\rho}$ where ϕ and ρ are the proportion of honest and strategic sellers that decide to enter the market. For higher prices, proportionally more strategic sellers would like to enter the market, resulting in lower γ. It is easy to show that there is a unique solution to Equations (1) and (2), thus a unique equilibrium of the model.

At equilibrium, we have the following comparative statics results:

Proposition 1 *More generous buyer protection (greater w) will reduce the equilibrium level of trust (γ) and push up the market price (p).*

[7] Figures 1 and 2 depict the case when $\frac{V}{3} \leq e \leq V$. When $0 \leq e < \frac{V}{3}$, it is a corner solution in which the probability of sale is one. But all of our propositions hold in this special case as well.

As shown in Figure 1, buyer willingness to trade increases with the coverage rate of buyer protection (w). Greater w moves curve (1) leftwards to (1') but leaves curve (2) unchanged, resulting in lower γ and higher p. Intuitively, higher willingness to trade motivates higher price but higher price attracts entry. In equilibrium, there is more cheating because relatively more strategic sellers are attracted to enter the market, although the probability of cheating conditional on entry $(1 - \frac{n}{C})$ does not change for each strategic seller.

Proposition 2 *Harsher punishment (greater A) increases both the equilibrium level of trust (γ) and the market price (p).*

In Figure 1, more punishment for cheating (greater A) shifts curve (2) rightwards to (2') but leaves curve (1) unchanged, leading to higher p and higher γ. Intuitively, the enhanced equilibrium level of trust may come from two sources: first, stiffer penalty for cheating discourages strategic sellers from cheating; second, stronger punishment does not increase the expected profit of strategic sellers as much as honest sellers, thus lowering the ratio of strategic to honest sellers in the marketplace. In one extreme case, if the penalty for cheating is sufficiently large such that $n - n^2/(2C) \geq (V+e)/2$, then no strategic seller will cheat, so $\gamma = 1$ and $p = (V+e)/2$. On the other hand, if there is no penalty for cheating ($A = 0$), strategic sellers will always cheat and the likelihood of entry is the same for strategic and honest sellers ($\rho = \phi = 1$). Then in equilibrium $\gamma = \alpha$ and $p = \frac{(V+e)\alpha}{2[1-(1-\alpha)\tau w]}$.

Proposition 3 *More active buyer reporting (greater τ) has a positive effect on price (p) but an ambiguous effect on the equilibrium level of trust (γ).*

As can be seen from Figure 1, if buyers are more willing to report (higher τ), the expected reimbursement from the buyer protection policy (τI) and expected punishment ($n = \tau A$) will both increase, shifting both curves upwards. This results in an increase in price (p) but an ambiguous effect on γ. Intuitively, from Propositions 1 and 2, expected reimbursement and expected punishment tend to work against each other on the equilibrium level of trust.

Proposition 4 *An increase in buyers' average valuation of high quality (V) will lead to higher prices (p) but lower equilibrium level of trust (γ).*

This result implies that it is more difficult to sustain trust in a market of more valuable goods. The intuition is simple from Figure 2. If the mean of buyer valuation increases (greater

V), sellers can charge higher prices, so curve (1) will move leftwards to (1'). Higher price attracts more strategic sellers to enter the market, reducing the overall level of trust in the market.

Proposition 5 *The positive effect of buyer protection on price will increase with the penalty for cheating (A), but greater A may increase or decrease the negative effect of buyer protection on equilibrium trust. Conversely, the positive effect of cheating penalty (A) on price will increase with the coverage of buyer protection, but more generous coverage may increase or decrease the positive effect of A on equilibrium trust.*

According to Propositions 1 and 2, policies that target buyer trusting and seller trustworthiness affect price in the same direction, but work against each other on the equilibrium level of trust. Proposition 5 further suggests that these two policies are not independent: they reinforce each other on price but they can be substitutes or complements on trust depending on the shapes of curves (1) and (2). See the proof in the Appendix.

2.2 Discussions and Extensions

The ratio of honest to strategic sellers in the market is measured by

$$R = \frac{\alpha\phi}{(1-\alpha)\rho} = \frac{\alpha p}{(1-\alpha)(p - n + \frac{n^2}{2C})}.$$

Since $n < C$, R is decreasing in p and increasing in n. This is the key to understanding our main results. More generous buyer protection increases p but does not change n, and therefore lowers the ratio of honest to strategic sellers. Empirically, this implies that sellers that enter after the introduction of buyer protection are more likely than before to be strategic sellers. This prediction motivates us to examine seller cohorts depending on their time of entry into Eachnet. Interestingly, the effect of cheating penalty on the ratio of honest to strategic sellers is less clear, because it increases both n and p. Traders that enter after an increase in cheater penalty are less likely to cheat, but they are not necessarily less likely to be strategic sellers.

As for market size, the model predicts the relative ratio of sellers to buyers as

$$MS = \alpha\phi + (1-\alpha)\rho = \frac{V+e}{4eK}[p - (1-\alpha)(n - \frac{n^2}{2C})]$$

Assuming both buyer population and the population of potential sellers to be one, MS defines the number of listings on the platform. Because the model predicts constant probability of sale for each listing, $MS \cdot prob(sale)$ defines the number of completed listings (trading volume). We can show that MS increases with buyer protection because buyer protection pushes up price, but the impact of a cheating penalty on MS is ambiguous as the penalty pushes up price but may discourage strategic sellers from entry relative to honest sellers. It is difficult to test this prediction in our data because the model assumes that all buyers have already entered the market but new buyers kept flowing into the market in the early years of Eachnet. Nevertheless, the fact that buyer protection increases trade volume explains why Eachnet introduced buyer protection programs first, even though the level of trust may be lowered. In the middle of the Internet boom, the goal of fast expansion was a primary concern for many online trading platforms. As its momentum was established, Eachnet changed its almost universal buyer protection policy to more moderate coverage, and introduced a warning system to help curb the possible detrimental effect of buyer protection on trust.

Our basic model can be extended in different directions. One possibility not considered in the basic model is that buyer reporting may increase with the coverage of buyer protection because reimbursement is conditional on reporting cheating to Eachnet. The simplest way to model this scenario is assuming the reporting probability τ to be an increasing function of the coverage rate (w). Then the price function can be written as

$$p(\gamma, V, e, \tau, w) = \frac{0.5\gamma(V+e)}{1-(1-\gamma)\tau(w)w}. \tag{3}$$

The only difference between Equation (1) and (3) is $\tau(w)$ 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.

2.3 Predictions testable in the real data

To summarize, we present a rational expectation model in which trust forms endogenously in an environment with buyer protection, a cheating penalty, and imperfect reporting. Our model generates a set of predictions regarding how the equilibrium trust and price are affected by changes in buyer protection and cheating penalty. As discussed below, the empirical setting of Eachnet allows us to test the following predictions:

- More generous buyer protection leads to more seller cheating;

- Sellers that enter after the introduction of a more generous buyer protection policy are more likely to be strategic and therefore more likely to cheat;
- Sellers of higher-value products are more likely to cheat;
- Both seller reputation and the introduction of a warning system should work against the effect of buyer protection and curb cheating;
- Conditional on completion, price should increase with the genorosity of buyer protection;
- Taking into account completion rate and price, buyer protection should increase the expected revenue from selling (thus inviting entry); and
- The sensitivity of cheating behavior to reputation and the warning system may increase or decrease with buyer protection.

Note that some theoretical predictions are difficult to test with the Eachnet data (e.g. trust-promoting policies increase trading volume) either because a universal introduction of trust-promoting policies collinears with time or because volume growth may differ across different categories for unobserved reasons, even if the trust-promoting policies are category-specific. We will discuss identification in detail after describing the data.

3 Background and Data Description

3.1 Background

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 after 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 high-cost 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 seller and 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 mails 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. This system is different from the eBay feedback system 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 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 the feedback system operates. Like eBay, Eachnet feedback score is based on the feedback reported by trading partners. A feedback, which is solicited by Eachnet 3-30 days after the completion of an online transaction, has three potential outcomes: 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. 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 "missing" and does not allow any subsequent change. This system is designed to minimize retaliation concerns that one may have when reporting a negative experience.

3.2 Buyer Protection and Seller Warning

To grow its market share and expand trade volume rapidly, Eachnet adopted a buyer protection program in October 2001. Upon a buyer 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, due to the sharply increasing burden on paying out reimbursement claims, Eachnet lowered the limit of reimbursement to 1000 RMB and imposed a deductible of 100 RMB per transaction. This system generates 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 can be reimbursed only up to 1000 after September 2002, a buyer paying 500 RMB can be reimbursed 400, and a buyer paying 100 RMB or less gets 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 blocks of transaction price. The second policy, especially the variation in coverage on 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 unidentifiable from the rapid market growth of Eachnet in the sample period.

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 to Eachnet. Upon 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, Eachnet warning is a threat to future activities and hence an implicit punishment for those who care about future access to Eachnet.

Unfortunately, the Eachnet warning was introduced for all transactions at the same time; thus, its impact is not identifiable from overall market growth. Instead of using Eachnet warning as a major policy treatment, we view seller recipient of the 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 only reflects one side's view and is independent of the official processing of the claim. Assuming that simultaneous posting of buyer and seller feedback has minimized the incentive of misreporting and retaliation, we view seller feedback as a product of actual seller behavior and the probability of the buyer reporting that behavior truthfully. Similarly, to the extent that Eachnet's independent investigation uncovers the truth and punishes misreporting, we view seller warning as a product of the seller's actual behavior and the probability of the buyer complaining truthfully to Eachnet. Seller warning and seller negative feedback can be positively correlated because they reflect the same behavior of the seller, or negatively because complaining to Eachnet (and receiving reimbursement) can be a strong substitute for filing negative feedback (without any tie to the buyer protection policy). In Section 4, we will elaborate how we identify changes in seller behavior and buyer reporting in response to the regime shift of buyer protection.

One caveat of our analysis is that the original data include feedback and warning information for both sides of the transaction but our model focuses on the incentive and behavior of sellers. To be consistent with the model, our empirical analysis focuses on feedback and warning outcomes for sellers only. As long as buyer reporting is truthful, seller receiving negative feedback or a warning indicates seller misbehavior, while not receiving negative feedback or a warning may reflect good behavior of seller, lack of reporting by buyer, or buyer not fulfilling his or her obligation in the transaction.

3.3 Data

Our Eachnet data contain a random sample of over 100,000 sellers and track each seller's complete selling history since 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 and seller distribution 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 results in a completed transaction, where online completion means a buyer has 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 exists. For each completed transaction, we observe four categories of information:

1) seller demographics including gender, age, income, occupation and region (if reported); [8] 2) seller history such as registration date, accumulated feedback score before the transaction, plus buyer feedback and the Eachnet warning on this transaction if there is any; 3) buyer information (same as that of the seller) [9]; and 4) information on the listed product, pricing method (auction vs. fixed price), auction format, the transaction price and transaction closing time.

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 outliers that have transaction price, reserve price or listing price over 100,000 RMB. The final sample has 76,607 unique sellers and 1,581,002 listings. On average, 62% of listings are completed. Conditional on completion, 59.91% has final price at or under 100 RMB, 33.42% between 100 and 1000 RMB, 4.96% between 1000 and 3000 RMB and only 1.71% above 3000 RMB.

Dividing the sample by three regimes of buyer protection, Table 2 presents regime-specific summary on market size, listing attributes, completion rate, seller reputation at the time of listing, and feedback/warning outcomes. Over time, the market has grown rapidly in the number of listings per month. 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 extremely high-priced items are sold on Eachnet. Over time, sellers become more likely to sell newer items, post pictures, quote buy-it-now prices, and become less likely to use bold fonts or auction. As expected, seller scores increase over time. Possible explanations are that reputable sellers are more likely to stay and later cohorts of new sellers behave better than old cohorts. Throughout the paper, we will group missing, zero, and negative score as "fishy" scores. Completion rate increases significantly from 35.59% in regime 0 to 62.06% in regime 1 and then remains stable at 64.19% in regime 2.

The bottom panel of Table 2 shows that, conditional on completion, the average final price drops steadily from regime 0 to regime 2, probably because listings grow faster on lower-value items. In terms of feedback, sellers are more likely to receive feedback in regimes 1 and 2

[8] 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%).

[9] 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.

than in regime 0. Conditional on receiving any feedback, sellers receive more positive feedback and less negative feedback over time. However, seller warnings increase across the latter two regimes. A possible explanation is that feedback and warnings are driven by different incentives in reporting. All these patterns are not necessarily caused by the introduction or revision of buyer protection. They could be driven by the natural development of the feedback score system or organic market growth. It is also shown that the likelihood of inter-region trading increases steadily over time, which reflects the geographic expansion of online transactions and greater willingness to trust long-distance trading partners.

To better identify the effect of buyer protection, we exploit differential regime changes by final price conditional on completion, namely $0-100$, $101-1000$, $1001-3000$ and above 3000 RMB. The average seller feedback (counting missing and neutral feedback as the third group besides positive and negative) is plotted against time by price group, with the monthly percentage of sellers receiving positive feedback in Figure 3 and negative feedback in Figure 4. Both figures show a strong and non-linear trend throughout the whole market, which highlights the importance of controlling for overall market growth.

At the transaction level, Table 3 summarizes seller's positive feedback, negative feedback and Eachnet warning by price range. Consistent with our theory (Proposition 4), it is more difficult to receive positive feedbacks for high value items. Although the second buyer protection policy (adopted in September 2002) eliminates coverage on items with value below 100 RMB, the feedback difference between 0-100 and 100-1000 RMB hardly changes after the policy. After Eachnet started the warning system in February 2002, seller warnings grew and then fluctuated around 1% for 0-100 RMB items and 1.5% for 100-1000 RMB items. As shown in Figure 5, the seller warning rate is higher for higher-value items and the difference across different groups of value increased to some extent soon after Eachnet revised its buyer protection policy in September 2002.

One important part of the theory is endogenous entry of sellers. To examine how different buyer protection regimes may attract different sellers to enter, we classify sellers into three groups: Cohort 0 refers to traders who registered on Eachnet on or before September 30, 2001 (i.e. in regime 0); Cohort 1 refers to traders who registered on Eachnet between October 1, 2001 and August 31, 2002 (i.e. in regime 1); and Cohort 2 refers to traders who registered on Eachnet after September 1, 2002 (i.e. in regime 2). As shown in Table 4, there are 17595 unique sellers in Cohort 0, 25639 in Cohort 1, and 15181 in Cohort 2. Their listing activity across the four price ranges is similar to the overall market. In terms of transaction outcome, Cohort 0 is most likely to receive negative feedback, Cohort 1 is most likely to receive positive feedback and Cohort 2 is most likely to receive warnings. These patterns are likely driven by the overall market trend as well as changes in trust-promoting policies. Therefore, we need to control for the overall market growth in the empirical analysis below.

4 Econometric Specifications

As in the theory, we consider empirical outcomes backwards. Conditional on completing the online part of the transaction, the buyer is expected to move first by paying for the item and then the seller decides on whether to deliver the item as promised. In the model, we assume that every buyer pays because it is embedded in buyer acceptance of seller offer. In reality, the time lag between winning the item online and payment 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, the observable outcome on sellers (either feedback or warning) should be interpreted as a proxy reflecting 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. For transaction i, we denote:

w_i = extent of buyer protection on item i;

p_i = transaction price agreed online;

X_i = item attributes such as product type, picture, font, auction format and other features used in the listing;

S_i = seller attributes such as gender, Eachnet score, and seller region;

B_i = seller attributes such as gender, Eachnet score, buyer region and whether the same region as the seller;

$\Phi(.)$ = logit function $= \dfrac{exp(.)}{1 + exp(.)}$.

We further define:

$$
\begin{aligned}
PR^s_{cheat} &= prob(\text{seller cheats}) \\
&= \Phi(\beta^s_0 + \beta^s_w \cdot w_i + \beta^s_p \cdot p_i + \beta^s_x \cdot X_i + \beta^s_b \cdot B_i + \beta^s_s \cdot S_i) \\
PR^b_{rpt+} &= prob(\text{buyer reports positive on seller} \mid \text{ seller does not cheat}) \\
&= \Phi(\alpha^b_0 + \alpha^b_p \cdot p_i + \alpha^b_x \cdot X_i + \alpha^b_b \cdot B_i + \alpha^b_s \cdot S_i) \\
PR^b_{rpt-} &= prob(\text{buyer reports negative on seller} \mid \text{seller cheats}) \\
&= \Phi(\gamma^b_0 + \gamma^b_w \cdot w_i + \gamma^b_p \cdot p_i + \gamma^b_x \cdot X_i + \gamma^b_b \cdot B_i + \gamma^b_s \cdot S_i) \\
PR^b_{complain} &= prob(\text{buyer complains to Eachnet about seller} \mid \text{seller cheats}) \\
&= \Phi(\lambda^b_0 + \lambda^b_w \cdot w_i + \lambda^b_p \cdot p_i + \lambda^b_x \cdot X_i + \lambda^b_b \cdot B_i + \lambda^b_s \cdot S_i)
\end{aligned}
$$

The likelihood of each possible feedback or warning outcome is:

$$
\begin{aligned}
L^s_{\text{pos feedback}} &= (1 - PR^s_{cheat}) \cdot PR^b_{rpt+} \\
L^s_{\text{neg feedback}} &= PR^s_{cheat} \cdot PR^b_{rpt-} \\
L^s_{\text{no or neutral feedback}} &= 1 - (1 - PR^s_{cheat}) \cdot PR^b_{rpt+} - PR^s_{cheat} \cdot PR^b_{rpt-} \\
L^s_{\text{warning}} &= PR^s_{cheat} \cdot PR^b_{complain}
\end{aligned}
$$

Ideally, one would want to recover all structural parameters by maximum likelihood, but this estimation is under-identified because a typical variable (e.g. X_i) enters all four structural probabilities ($PR^s_{cheat}, PR^b_{rpt+}, PR^b_{rpt-}, PR^b_{complain}$) but one of the four observed outcomes is collinear with the rest – the likelihood of no or neutral feedback is exactly one minus the likelihood of positive feedback and negative feedback. As a result, it is not clear whether the impact of X_i on observed outcomes arises because X_i affects seller cheating or buyer reporting.

Although this identification problem applies to every variable that enters in all four structural probabilities, the effects of buyer protection can be identified through two assumptions: first, feedback and warning are proxies for the same behavior; second, buyer protection and warning targets misbehavior only and therefore they should not change the probability of reporting positive feedback conditional on good behavior. These two assumptions imply that we can use positive feedback to identify the effect of buyer protection on seller cheating.

Under these assumptions, we can derive the marginal effect of buyer protection on observed seller outcomes by running the following reduced-form regressions:

$$\begin{aligned}
1^s_{\text{pos feedback},i} &= \theta_{10} + \theta_{1w} \cdot w_i + \theta_{1p} \cdot p_i + \theta_{1x} \cdot X_i + \theta_{1b} \cdot B_i + \theta_{1s} \cdot S_i + \epsilon_{1it} \\
1^s_{\text{neg feedback},i} &= \theta_{20} + \theta_{2w} \cdot w_i + \theta_{2p} \cdot p_i + \theta_{2x} \cdot X_i + \theta_{2b} \cdot B_i + \theta_{2s} \cdot S_i + \epsilon_{2it} \\
1^s_{\text{warning},i} &= \theta_{30} + \theta_{3w} \cdot w_i + \theta_{3p} \cdot p_i + \theta_{3x} \cdot X_i + \theta_{3b} \cdot B_i + \theta_{3s} \cdot S_i + \epsilon_{3it}.
\end{aligned}$$

According to our structural setup, we have

$$\begin{aligned}
\theta_{1w} &= \frac{\partial L^s_{\text{pos feedback}}}{\partial w} \\
&= -\beta^s_w \cdot PR^s_{cheat} \cdot L^s_{\text{pos feedback}} \\
\theta_{2w} &= \frac{\partial L^s_{\text{neg feedback}}}{\partial w} \\
&= (\beta^s_w \cdot (1 - PR^s_{cheat}) + \gamma^b_w \cdot (1 - PR^b_{rpt-})) \cdot L^s_{\text{neg feedback}} \\
\theta_{3w} &= \frac{\partial L^s_{warning}}{\partial w} \\
&= (\beta^s_w \cdot (1 - PR^s_{cheat}) + \lambda^b_w \cdot (1 - PR^b_{complain})) \cdot L^s_{warning}.
\end{aligned}$$

In other words, regressing seller's positive feedback on the extent of buyer protection will yield a coefficient (θ_{1w}) that indicates the sign of how buyer protection affects seller behavior (β^s_w); regressing seller's negative feedback or warning on buyer protection could generate results different from that of positive feedback due to the effect of buyer protection on reporting (γ^b_w) and complaining (λ^b_w). We are not able to determine the sign and magnitude of γ^b_w and λ^b_w because the exact magnitudes of $PR^s_{cheat}, PR^b_{rpt+}, PR^b_{rpt-}, PR^b_{complain}$ are not identified. That said, a consistent finding of $\theta_{1w} < 0, \theta_{2w} > 0, \theta_{3w} > 0$ suggests that the positive effect of buyer protection on negative feedback and warning is at least partly driven by increased seller cheating.

All the above specifications focus on trading outcomes after a transaction has been completed online with finalized transaction price. Our theory also has a clear prediction regarding the impact of buyer protection on price, which leads to $\theta_{4w} > 0$ in the following reduced-form regression:

$$log(P_i) = \theta_{40} + \theta_{4w} \cdot w_i + \theta_{4x} \cdot X_i + \theta_{4b} \cdot B_i + \theta_{4s} \cdot S_i + \epsilon_{4i}.$$

Due to specific assumptions on buyer value and seller cost (i.e. uniform), the theory predicts that completion rate is unchanged with buyer protection or seller penalty. These assumptions are unlikely to hold in reality. Therefore, we have no clear prediction on θ_{5w} in the following regression:

$$1_{completed,i} = \theta_{50} + \theta_{5w} \cdot w_i + \theta_{5x} \cdot X_i + \theta_{5b} \cdot B_i + \theta_{5s} \cdot S_i + \epsilon_{5i}.$$

However, if buyer protection attracts strategic sellers to enter (as the theory predicts), the effect of buyer protection on the seller's expected revenue – which is equal to the effect on completion rate times the effect on price if completed ($\frac{\theta_{5w}}{prob(complete)} + \theta_{4w}$) – must be positive. This is testable in the data.

5 Empirical Tests

To follow the logic of theoretical derivation, we will first report results on seller feedback and warning, and then move on to transaction price conditional on completion. The last subsection will provide supplemental evidence on completion rate.

5.1 Seller Feedback and Warning

This subsection tests four key predictions on sellers' cheating behavior: (1) More generous buyer protection leads to more seller cheating; (2) Sellers that enter after the introduction of buyer protection are more likely to be strategic and therefore more likely to cheat; (3) Sellers of higher-value products are more likely to cheat; and (4) Both seller reputation and the introduction of warning system should work against the buyer protection effect and curb cheating.

Table 5 presents results on three trade outcomes, namely whether a seller receives negative feedback, positive feedback, or Eachnet warning on a particular transaction. We report results from the linear probability model, controlling for a large number of product category fixed effects (a 3-level category code which is detailed to the brand name of a specific type of product, for example, a Minolta camera), seller region fixed effects (at the city level), buyer region fixed effects (by city), and year-month fixed effects. A non-linear binary model may suffer from the incidental parameter problem, although we have tried logit with exactly the same controls and obtain similar results.

The variables of key interest are three specific variables created to capture the percentage of the final price covered by buyer protection in different regimes. Based on Table 1, the first variable, "fully covered ($0 < p <= 100$)", is a dummy equal to 1 if the price of the product falls between 0 and 100 RMB and the transaction occurs in regime 1. The second variable, "% covered ($100 < p <= 1100$)", is equal to 0 in regime 0, 1 in regime 1 and $(p - 100)/p$ in regime 2 if the final price falls between 101 and 1100 RMB. The third variable, " % covered ($p > 1100$)" which applies to the price range greater than 1100 RMB, is equal to 0 in regime 0, $min(p, 3000)/p$ in regime 1 and $1000/p$ in regime 2. Controlling for year-month fixed effects, these three coverage variables enable us to differentiate the effect of buyer protection from overall market growth over time. We also include seller reputation measures, i.e., the log of seller scores and a dummy variable indicating whether the seller score is "fishy" (including missing, negative, or zero scores).

In addition to product-category fixed effects, seller-region fixed effects, buyer-region fixed effects, year-month fixed effects and day of week fixed effects, all regressions control for the final price, the final price squared, and final price interacting with count of month since June 2001. These price terms intend to capture the possibility that a market without buyer protection could have different tendency of seller cheating or buyer reporting at different product values and this tendency could trend differently for different prices. Other controls include seller's Eachnet age (days since registration), # of completed listings the seller had by the time of listing, buyer's Eachnet age, buyer feedback scores, and listing attributes.

A consistent picture emerges from Table 5 across different outcome measures. All the three coverage variables have expected signs (except for one case) and are significant at the 1 percent level in most cases. We find that the higher the coverage, the more (less) likely it is that sellers will get negative (positive) feedback, and the more likely they are to receive warnings. While the results for negative feedback and warnings may be subject to changes in buyer reporting, we cannot think of any reason why a buyer may report positive feedback differently across buyer protection regimes conditional on good seller behavior. Therefore, the results on positive feedback strongly suggest that the introduction of buyer protection makes sellers less trustworthy on the market. This is consistent with Proposition 1. The consistency between positive feedback and other outcomes suggests that the increase in negative feedback and warnings under more generous buyer protection is partly driven by increased seller cheating.

We also find that when the transacted product moves from the first coverage group (0-100) to the third group (above 1100), the negative effect on seller trustworthiness becomes larger in absolute value. This means that strategic sellers are more likely to focus on high-price items. This is consistent with Proposition 4, which predicts that an increase in buyers' average valuation of high quality leads to less trustworthiness of sellers.

Besides the above supportive result, Table 5 provides suggestive evidence that the introduction of buyer protection induces strategic sellers to enter the market. Two variables, "cohort 1" and "cohort 2", which represent the group of sellers entering the market during regimes 1 and 2 respectively, are included in the regressions of columns (4) and (8) in Table 5. As shown in column (8) in Table 5, the estimated coefficients on Cohort 1 and Cohort 2 are both negative, and significant in "cohort 1" (corresponding to more generous buyer protection), suggesting that the sellers entering after buyer protection are less likely to receive positive feedback.

We are also interested in how a penalty on cheating behavior affects seller behavior. To look at this effect, we rely on two measures: seller reputation and the introduction of the Eachnet warning after February 2002. Reputable sellers have more to lose if they cheat on buyers, so we expect more reputable sellers to be more trustworthy. Similarly, our theory predicts that the introduction of Eachnet warning will motivate sellers to be more trustworthy.

Table 5 offers evidence for these predictions. First, for those sellers with positive scores, they receive less negative feedback and warnings and more positive feedback if their feedback scores are higher. These effects are all significant at the one percent level. For those who have missing, negative, or zero scores and are probably more likely strategic sellers, their chance to get negative (positive) feedback and warnings is larger (smaller) than those who have earned positive scores. Second, even though new seller cohorts that entered Eachnet after the introduction of buyer protection are more likely to cheat, the introduction of the Eachnet warning makes them behave better. This result is shown in the negative and significant sign of the interaction between Cohort 1 and "aftwarning" – a dummy equal to one after Eachnet warning was in place – in column (4) and positive and significant sign of the same interaction in column (8).

Another interesting result is that the introduction of both the Eachnet warning and buyer protection reduces the positive effect of reputation on seller trustworthiness: while the seller positive scores have negative (positive) effect on negative (positive) feedbacks, given the level of seller scores (log), the introduction of Eachnet warning or buyer protection makes sellers more (less) likely receive negative (positive) feedbacks. The result is similar in the case of seller warnings. In other words, the trust-promoting polices serve as substitutes for seller reputation.

One may argue that the identified effects of buyer protection may be driven by some unobserved factors that exist even before the introduction of buyer protection. To address this concern, we conduct two placebo tests. Specifically, we focus on the sample prior to regime 1 (i.e., before October 2001) and pretend that the first buyer protection policy was introduced in August 2001. Columns (1) and (3) in Table 6 report the estimated effect of placebo policy on seller feedback. We do not find any significant results on the three coverage variables, and the signs of their coefficients are not consistent. We then pretend that the second buyer protection policy was introduced in August 2001. In this case, the items with prices less than 100 RMB would not be insured by the policy and their effect on seller trustworthiness is not identifiable from the effect of the time trend. Columns (2) and (4) report the results. Again, all the coefficients are not significant except for the second coverage variable which has a significant and *positive* sign in the case of seller positive feedbacks. But this finding goes against our theoretical prediction. Both placebo tests suggest that our results in Table 5 are unlikely to be driven by some unobserved forces before the introduction of buyer protection.

5.2 Transaction Price

Now we turn to testing the prediction regarding the effects of buyer protection and warnings on transaction price. Our theory has that unambiguous prediction that the effects will be positive. However, we face a serious challenge while conducting such an empirical test. The main challenge lies in the fact that our definition of coverage differentiation under different regimes of buyer protection depends directly on the price of the transacted product. So when log of transaction price becomes the dependent variable, the three coverage variables must be correlated with the error term in the estimation equation.

To address this, we classify products according to 3-level product categories so that we can compare consistently high-price categories (that likely follow the buyer protection policy for above 1100) with consistently low-price categories (that likely follow the buyer protection policy for under 100) and other categories. More specifically, we compute the distribution of final price for each product category. A category is labeled low price if it has at least 100 completed transactions and the 90th percentile of its price distribution is below 100 RMB. A category is labeled high price if it has at least 100 completed transactions and the 25th percentile of its price distribution is above 1100 RMB.[10] By this definition, we have 97 low price categories accounting for 14.5% of completed listings, 8 high price categories accounting for 1.1% of completed listings, and the other 560 categories for the rest of the sample. The Appendix Table lists the names of the top-10 low price categories (with the highest number of completed listings), all of the 8 high price categories, and another two categories that are of very high price but do not have enough completed listings to fall under our definition of high price categories.

[10]Only one category has the 10th percentile above 1100 RMB.

Table 7 presents regression results on transaction price. Note that the regression has controlled for a long list of factors that may influence transaction prices, including product category fixed effects, year-month fixed effects, day of week fixed effects, linear trend for each level-1-product-category[11], seller age, number of completed listings the seller had by the time of listing, seller-region fixed effects, and listing attributes. We do not control for the specific value of buy-it-now price because in many cases it is exactly the dependent variable but the existence of buy-it-now and of reserve price are controlled. We do not control for buyer attributes either because the listing is open for all potential buyers and buyer attributes are equilibrium outcome.

It is clear that buyer protection – now defined by the interaction of regime 1 and product categories[12] – pushes up transaction price: when a product in low price categories moves from regime 0 to regime 1, its price increases by about 2.5 percent. The corresponding number for high-price categories is 7.3 percent. These effects are all significant at the 5-percent level. Sellers with positive scores enjoy some degree of price premium. Counter-intuitively, those with "fishy" scores also enjoy a price premium (as compared to those with scores equal to 1). One possible interpretation is that sellers with inferior records target high-price items or bluff about product quality even though the chance of completing the transaction is small. We will come back to this issue when we examine completion rate.

So far, we have found several interesting empirical results: (1) buyer protection leads to more seller cheating; (2) trust-promoting policies, both buyer protection and warnings, make seller trustworthiness less sensitive to seller reputation; (3) seller cohorts that enter after the buyer protection program are more likely to cheat but such cheating incentives are corrected by the introduction of the warning system; (4) transaction price increases with the degree of buyer protection. These results lend strong support to our theory.

5.3 Supplementary evidence from completion rate

For model tractability, our theory adopts specific assumptions as to buyer value and seller cost (i.e. uniform) and predicts that neither buyer protection nor seller penalty affects completion rate. These assumptions are unlikely to hold in reality. Putting it another way, in the theory, all the potential gain from cheating is embedded in equilibrium price, but in our data, gain from

[11] Level 1 category code is the most crude classification of categories in the original data. For example, a Minolta camera will have a level-1 code 33 (for image-related electronics), level-2 code 01 (for digital camera) and level-3 code 11 (for the brand of Minolta). Every listing of a Minolta camera will have a 3-level category code of 330111.

[12] Regime 2 * low price categories and regime 2 * high price categories are dropped due to collinearity.

cheating can be reflected in price, completion rate, or both. Since we already found evidence for a positive effect of buyer protection on price, a priori we do not know whether buyer protection will increase or decrease completion in the data.

Table 8 presents regression results on whether a listing is completed, using the same controls as in the price regression. By definition, the sample includes all listings while all the other regressions presented above use only completed listings. Column 1 shows that the introduction of buyer protection in regime 1 decreases the likelihood of completing a listing if the listing is in a low-price category but increases the likelihood if the listing is in a high-price category. Both coefficients are significant at the 5 percent level, but their magnitudes are small (-1% and 1.3%). These coefficients, together with the estimated price increase after buyer protection (2.5% for low price categories and 7.3% for high price categories), suggests that the overall effect of buyer protection on seller expected revenue is positive. If a strategic seller cheats in regime 1 (with zero cost of producing junk item), he could earn more profit and therefore should be more likely to enter the market ex ante. This is consistent with our theory.

In contrast to the small coefficients of coverage variables, seller score has a huge effect on completion, with more positive scores leading to higher completion and "fishy" scores leading to lower completion (as compared to scores equal to 1). The coefficient on whether seller score is "fishy" implies that having missing, negative, or zero score can reduce the probability of completion as much as 39.7 percent. Combined with the large positive coefficient of this variable on final price (Table 7), it implies that sellers with "fishy" scores have lower revenue on average and try to compensate for their low completion rate by charging relatively high price. This interpretation is consistent with Jin and Kato (2006), who show that cheating is more likely when sellers make stronger claims of product quality. It is also consistent with Table 5 in that "fishy" sellers tend to get more negative feedback, fewer positive feedback, and more warnings.

Column (2) includes the interaction of buyer protection availability and seller score variables. They are both negative, suggesting that completion rate is less sensitive to positive scores but more sensitive to "fishy" scores after the introduction of buyer protection. Columns (3) and (4) add the interaction of after warning and seller score variables to columns (1) and (2) respectively. Again, these interactions are negative and significant, suggesting that completion rate is less sensitive to positive seller score and more sensitive to "fishy" scores after Eachnet introduced the warning system. The increased sensitivity on "fishy" scores can be explained by consumers being more cautious about "fishy" sellers as more institutions are incorporated to boost trust. Another possibility is that as Eachnet grows, a smaller fraction of sellers have "fishy" scores, which makes "fishy" score more alarming than before.

6 Conclusion

A growing body of literature has emphasized the importance of trust. It is equally, if not more, important to ask how to enhance trust. In rational expectation models, trusting is always equal to trustworthiness. However, a trust-promoting policy may function differently depending on whether it targets buyer trusting or seller trustworthiness. In this paper, we first develop a simple rational expectation model and then analyze data from the early years of Eachnet. Our analysis shows that trust-promoting institutions such as buyer protection actually can lead to a lower level of trust. This finding suggests that one should avoid making proposals to enhance "trusting" without providing institutional incentives to enhance trustworthiness. As trusting and trustworthiness interact in equilibrium, trust cannot be enhanced until strategic players are induced to behave more honestly.

A follow-up question is how to design an optimal trust-building policy. While buyer protection alone will not boost trust in equilibrium, is there an optimal combination of buyer protection and seller penalty? The answer to this question depends on who is the decision maker and what objective function she is aiming for. From the perspective of a platform, its profits depend on trading price and trading volume directly, regardless of whether the trade is fair or spoiled by seller cheating. However, from a social planner's point of view, the trade does not generate any net gain until the seller delivers the good as promised. Although the platform cares about equilibrium trust in the long run (because it affects price and volume), it is not difficult to show that a profit-maximizing platform puts more weight on price and volume than the social planner. The divergence is even greater if the platform's goal is to expand as soon as possible and make the platform attractive to venture capitalists or potential acquirers. This helps explain why, in an era of Internet boom, Eachnet adopted buyer protection before introducing the warning system. How to motivate a platform to maximize the social gain of trade is a topic for future research.

References

[1] Aghion, Philippe, Yann Algan, Pierre Cahuc, and Andrei Shleifer, 2010, "Regulation and Distrust." *Quarterly Journal of Economics* 125(3): 1015-1049.

[2] A'Hearn, Brian, 2000, "Could Southern Italians Cooperate? Banche Popolari in the Mezzogiorno," *Journal of Economic History* 60(1): 67-93.

[3] Alesina, Alberto, and Eliana La Ferrara, 2002, Who Trusts Others? *Journal of Public Economics* 85(2):207-34.

[4] Algan, Yann, and Pierre Cahuc, 2010, "Inherited Trust and Growth." *American Economic Review* 100(5):2060-2092.

[5] Arrow, Keneth, 1972, "Gifts and Exchanges," *Philosophy and Public Affairs* 1: 343-362.

[6] Barr, Abigail, 2003, "Trust and Expected Trustworthiness: Experimental Evidence from Zimbabwean Villages, " *Economic Journal* 113(489): 614-630.

[7] Bajari, Patrick, and Ali Hortacsu, 2004, "Economic Insights from Internet Auctions," *Journal of Economic Literature* 42(2): 457-486.

[8] Bolton, Gary E.; Elena Katok and Axel Ockenfels, 2004, "How effective are online reputation mechanisms? An experimental study, ," *Management Science* 50(11): 1587-1602.

[9] Bohnet, Iris, and Steffen Huck, 2004, "Repetition and Reputation: Implications for Trust and Trustworthiness When Institutions Change," *American Economic Review* 94(2): 362-366.

[10] Buchan, Nancy and Rachel Croson, 2004, "The Boundaries of Trust: Own and Others Actions in the US and China," *Journal of Economic Behavior and Organization* 55: 485-504.

[11] Dellarocus, Chrysanthos, 2003, "The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms," *Management Science* 49(10): 1407-1424.

[12] Fukuyama, Francis, 1995, *Trust*. New York: Free Press.

[13] Glaeser, Edward L., David I. Laibson, Jose A. Scheinkman and Christine L. Soutter, 2000, "Measuring Trust," *Quarterly Journal of Economics* 115 (3): 811-846.

[14] Greif, Avner, 1993, "Contract Enforceability and Economic Institutions in Early Trade: The Maghribi Traders," *American Economic Review* 83(3): 525-548.

[15] Guiso, Luigi, Paola Sapienza and Luigi Zingales, 2004, "The Role of Social Capital in Financial Development," *American Economic Review* 94(3): 526-556.

[16] ——, 2006, Dose Culture Affect Economic Outcomes? *Journal of Economic Perspectives* 20(2):23-48.

[17] ——, 2008, Alfred Marshall Lecture: Social Capital as Good Culture. *Journal of the European Economic Association* 6(2-3):295-320.

[18] Jin, Ginger Z. and Andrew Kato, 2006, "Price, Quality and Reputation: Evidence From An Online Field Experiment," *RAND Journal of Economics* 37(4): 983-1005.

[19] Karlan, Dean, 2005, "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions," *American Economic Review* 95(5): 1688-1699.

[20] Knack, Stephen, and Philip Keefer, 1997, "Does Social Capital Have an Economic Payoff? A Cross-Country Investigation," *Quarterly Journal of Economics* 112(4): 1251-1288.

[21] La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert Vishny, 1997, Trust in Large Organizations. *American Economic Literature* 46(2): 285-332.

[22] Putnam, Robert, 1993, *Making Democracy Work: Civic Traditions in Modern Italy.* Princeton, NJ: Princeton University Press.

[23] Resnick, Paul and Richard Zeckhauser, 2002, "Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System," In the *Economics of the Internet and e-Commerce*, M.R. Baye, Ed. *Advances in Applied Microeconomics*, vol. 11. Elsevier Science, Amsterdam, 127-157.

[24] Tabellini, Guido, 2010, Culture and Institutions: Economic Development in the Regions of Europe." *Journal of the European Economic Association* 8(4): 677-716.

[25] Zak, Paul J., and Stephen Knack, 2001, Trust and Growth. *Economic Journal* 111(470): 295-321.

7 Appendix: Solution to the Model

We solve the model by backward induction. In stage 3, a strategic seller will cheat if $c \geq n = \tau A$. With sufficient penalty ($n \geq C$), all strategic sellers will not cheat; we assume $n < C$ to avoid this trivial case. 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 $v \leq \bar{v} = \frac{p-(1-\gamma)\tau w p}{\gamma}$. 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 Eachnet buyer protection 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.[13] Setting a price p will generate for an honest seller the expected profit:

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

The optimal price has an inner solution when $\frac{V}{3} \leq e \leq V$ and a corner solution when $0 \leq e < \frac{V}{3}$:

$$p(\gamma, V, e, \tau, w) = \begin{cases} \frac{0.5\gamma(V+e)}{1-(1-\gamma)\tau w}, & \frac{V}{3} \leq e \leq V, \\ \frac{\gamma(V-e)}{1-(1-\gamma)\tau w}, & 0 \leq e < \frac{V}{3}. \end{cases}$$

For both solutions, it's 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 when $\frac{V}{3} \leq e \leq V$, and turn to the other case when it is necessary. At the optimal price, the probability of sale is $\frac{V+e}{4e}$ and the expected profit of an honest seller is $\pi^H = \frac{V+e}{4e}p$. [14]

[13] Otherwise their prices will reveal their strategic type to the buyers, and their optimal "deviation" prices must be lower than the honest sellers' price because buyers know that strategic sellers only provide high quality products when $c < n$. Clearly such deviations from the honest sellers' price are not in the interests of strategic sellers.

[14] Probability of sale is equal to one in the corner solution when $0 \leq e < \frac{V}{3}$. It is also worth noting that, because we assume (1) buyers' valuation conforms to a uniform distribution and (2) honest sellers engage in monopoly pricing after being matched with a buyer, the optimal price incorporates buyer concern of cheating and Eachnet buyer protection. As a result, the impact of γ (trustworthiness) and w (buyer protection) on the probability of

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:

$$\pi^S = E_c\{[(p-c)\frac{n}{C} + (p-n)(1-\frac{n}{C})][\frac{V+e-\frac{p-(1-\gamma)\tau wp}{\gamma}}{2e}]\} = \frac{V+e}{4e}(p-n+\frac{n^2}{2C})$$

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

$$\pi^{SH} = E_c\{(p-c)[\frac{V+e-\frac{p-(1-\gamma)\tau wp}{\gamma}}{2e}]\} = \frac{p(V+e)}{8e}$$

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 $p = (V+e)/2$. This case is less interesting, so we rule it out by assuming $V + e > 2n$.

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 $K \geq \max\{\frac{(V+e)^2}{8e}, \frac{V^2-e^2}{4e}\}$. 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 the terms, we get

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

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 $p = (V+e)/2$ is greater than the endpoint of curve 2 at $p = n - n^2/(2C)$ by our assumption $V + e > 2n$.

The comparative statics results of Propositions 1-4 follow easily from examining changes in the two curves. For Proposition 5, we aim to prove $\frac{\partial^2 p}{\partial w \partial A} > 0$. From Equation (2), we have

$$\frac{1}{(1-\gamma)^2}\frac{\partial\gamma}{\partial w} = \frac{-\alpha(n-\frac{n^2}{2C})}{(1-\alpha)(1-\frac{n}{C})(p-n+\frac{n^2}{2C})^2}\frac{dp}{dw} \tag{4}$$

sale is completely offset by optimal pricing.

For convenience, let $G(p,n) = \frac{\alpha(n-\frac{n^2}{2C})}{(1-\alpha)(1-\frac{n}{C})(p-n+\frac{n^2}{2C})^2} > 0$. It's easy to prove $G(p,n)$ is increasing with n and decreasing with p.

From Equation (1), we have $\frac{\partial p}{\partial \gamma} = \frac{(V+e)(1-\tau w)}{2[1-(1-\gamma)\tau w]^2} > 0$ and $\frac{\partial p}{\partial w} = \frac{(V+e)\gamma(1-\gamma)\tau}{2[1-(1-\gamma)\tau w]^2} > 0$. Thus, given $\frac{dp}{dw} = \frac{\partial p}{\partial \gamma}\frac{\partial \gamma}{\partial w} + \frac{\partial p}{\partial w}$, from Equation (4), we may get

$$\frac{\partial \gamma}{\partial w} = \frac{-G(p,n)\frac{\partial p}{\partial w}}{\frac{1}{(1-\gamma)^2} + G(p,n)\frac{\partial p}{\partial \gamma}} < 0$$

$$\frac{dp}{dw} = \frac{(V+e)\gamma(1-\gamma)\tau}{2[1-(1-\gamma)\tau w]^2 + (V+e)(1-\tau w)(1-\gamma)^2 G(p,n)} > 0$$

Given $n = \tau A, 0 \leq \tau \leq 1$, just to simplify the notation, we may ignore τ as $\frac{\partial^2 p}{\partial w \partial A}$ and $\frac{\partial^2 p}{\partial w \partial n}$ share the same sign. Define $F(p,n) = \frac{(V+e)\gamma(1-\gamma)\tau}{2[1-(1-\gamma)\tau w]^2+(V+e)(1-\tau w)(1-\gamma)^2 G(p,n)}$, then $F(p,n)$ is increasing with p and decreasing with n. By implicit function theorem, we have

$$sign[\frac{\partial^2 \gamma}{\partial w \partial n}] = sign[\frac{\partial^2 \gamma}{\partial w \partial n}] = sign[-\frac{F_n}{F_p}] > 0.$$

This proves Proposition 5.

Figure 1:Equilibrium and Comparative Statics: Baseline Model

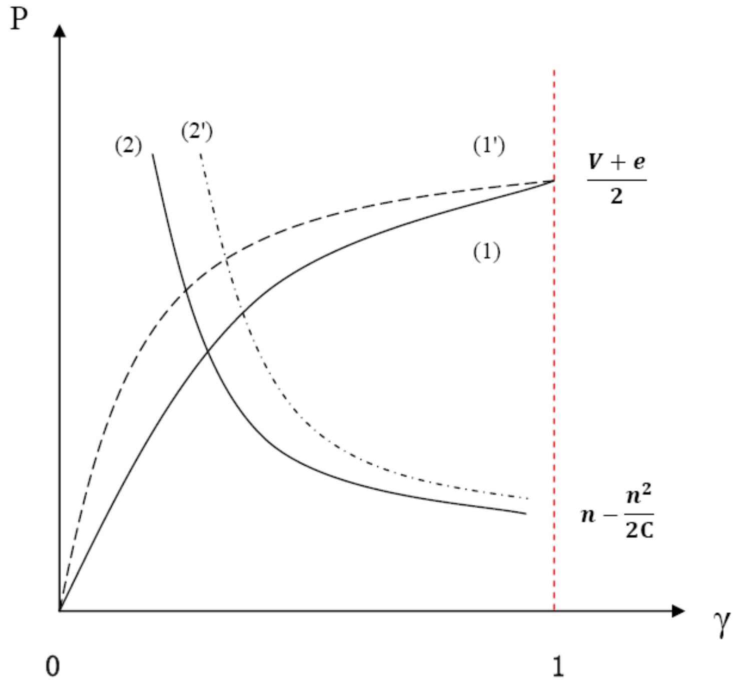

Figure 2:Comparative Statics for the Mean of Buyer Valuation (V)

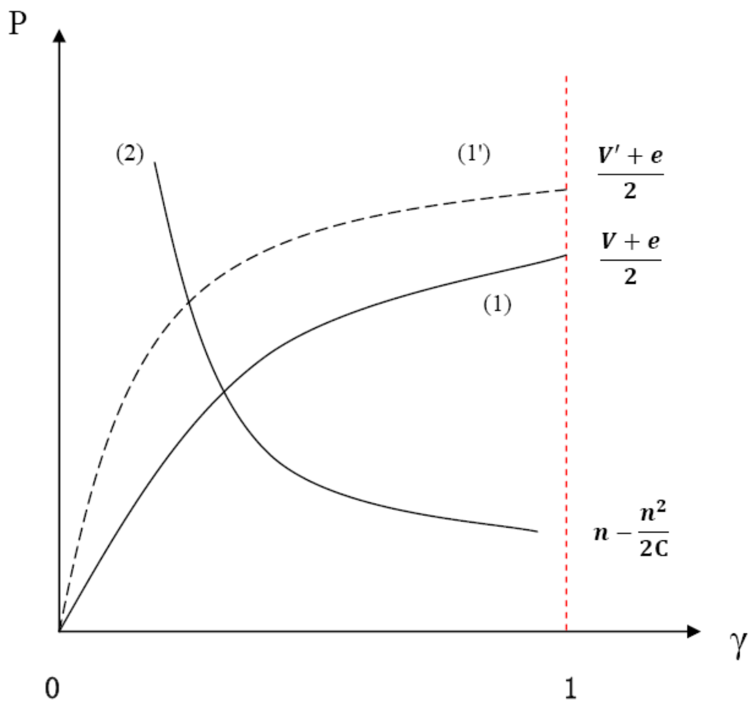

Figure 3:Seller Positive Feedback by Buyer Protection Regime

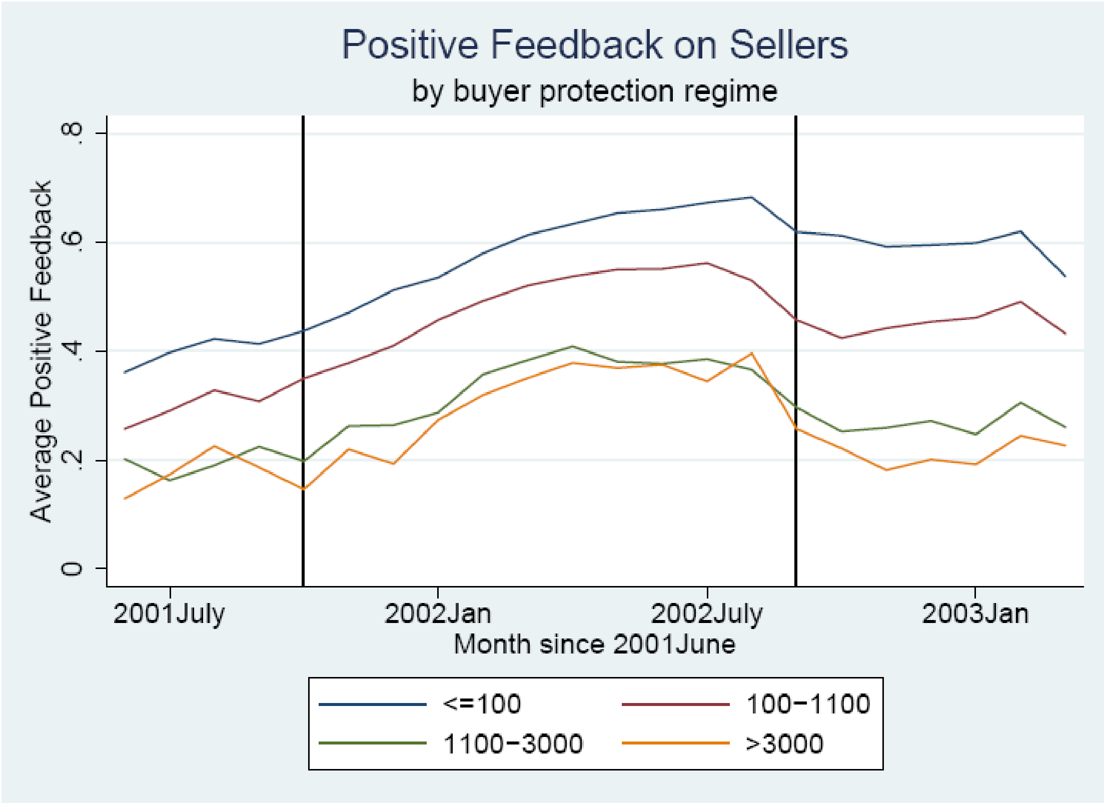

Figure 4:Seller Negative Feedback by Buyer Protection Regime

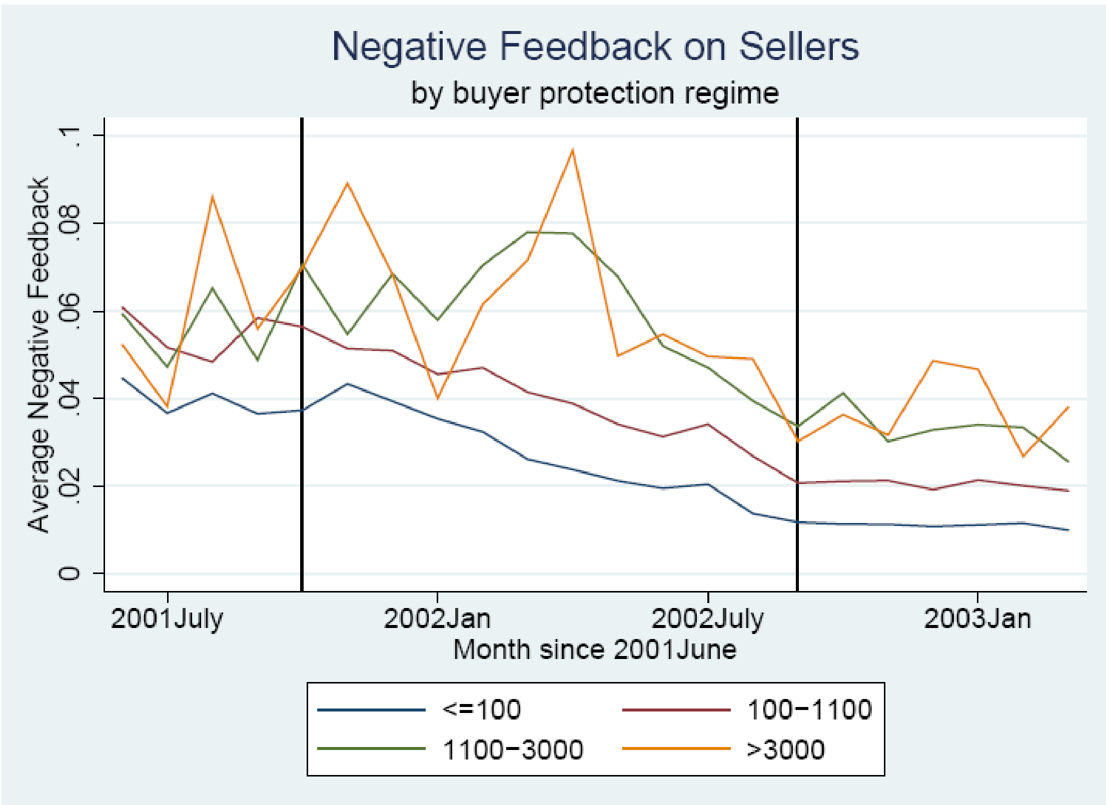

Figure 5:Seller Warning by Buyer ProtectionRegime

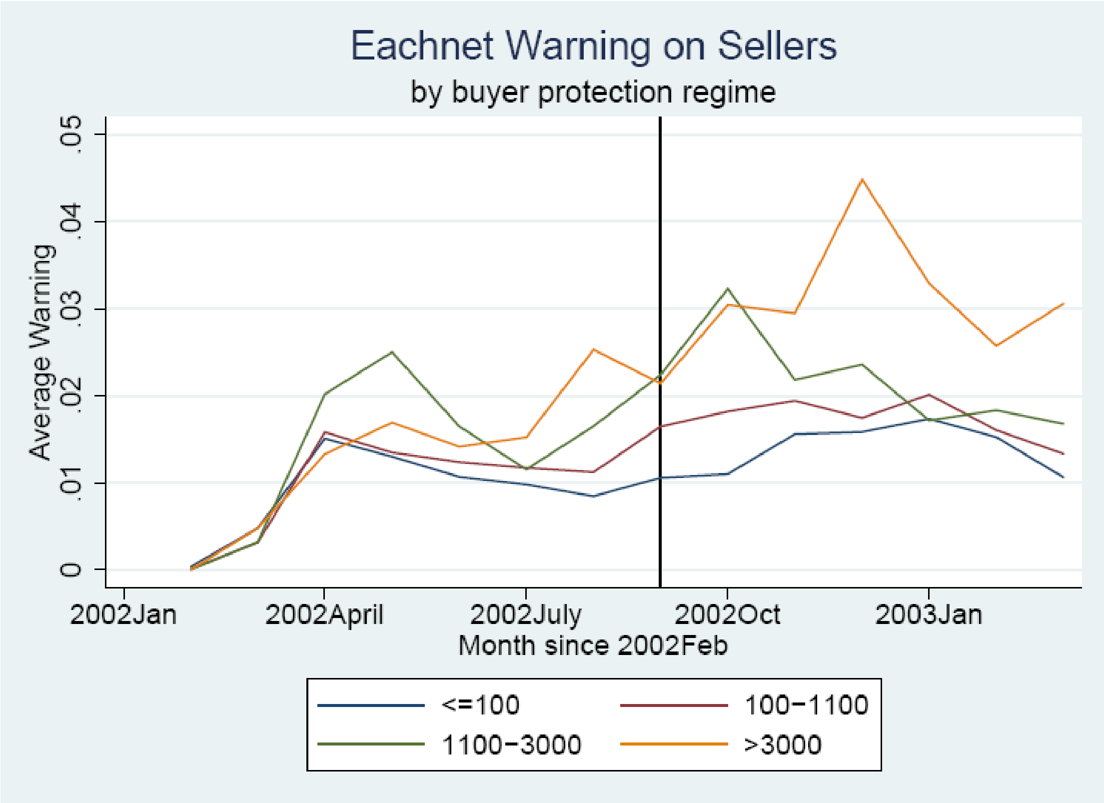

Table 1:Percentage of the PriceCovered by Buyer Protection

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 listings	78803	578528	923671
# of listings per month	19701	44502	131953
% with fixed p	51.76%	76.35%	86.21%
fixed p | have fixed p	932.11(150)	523.09(114)	350.46(90)
% with reservation price	49.16%	36.77%	23.11%
reservation price | have reservation p	1122.21(250)	741.64(173)	611.45(168)
starting price of auction	741.7(100)	317.79(60)	220.00(50)
% allow auction	100%	95.16%	88.50%
% have picture	40.54%	78.18%	86.06%
% have bold font	35.45%	15.03%	13.41%
condition of item			
new1	0.00%	0.00%	0.00%
new2	61.21%	78.39%	85.22%
new3	30.67%	17.42%	11.41%
new4	5.38%	2.32%	1.45%
new5	2.49%	1.60%	1.63%
new6	0.25%	0.27%	0.25%
seller age(days since registration)	111.45	224.50	273.14
buyer age(days since registration)|completion	39.86	109.69	118.96
# of completed listings by t	37.03	194.97	340.81
% seller score missing	62.92%	26.55%	23.08%
% seller score = 0	2.38%	1.06%	0.28%
% seller score < 0	3.05%	0.76%	0.15%
seller score | have score	8.50	85.60	160.59
seller score is fishy (i.e. missing, negative or zero)	68.35%	28.37%	23.51%
completion rate	35.59%	62.06%	64.19%
Conditional on completion			
% completion by auction	62.71%	48.47%	38.78%
final price	668.86(150)	423.83(90)	270.97(60)
% with any seller feedback	43.89%	64.20%	56.60%
% seller positive feedback	32.54%	56.72%	53.09%
% seller negative feedback	4.80%	3.13%	1.51%
% with seller warning(after 2/02 only)		1.03%	1.52%
same region	59.49%	44.55%	35.39%

Table 3:Summary Statistics of Seller Feedback and Warningsby Final Price and Buyer Protection Regime

Range of final price		Seller PositiveFeedback			Seller NegativeFeedback			Seller Warning	
		Regime 0	Regime 1	Regime 2	Regime 0	Regime 1	Regime 2	Regime 1	Regime 2
		6/01-9/01	10/01-8/02	9/02-3/03	6/01-9/01	10/01-8/02	9/02-3/03	10/01-8/02	9/02-3/03
0-100	mean	0.397	0.634	0.592	0.039	0.023	0.011	0.010	0.014
	sd	0.489	0.482	0.491	0.195	0.149	0.104	0.097	0.116
	frequency	12338	196375	378391	12338	196375	378391	172047	378386
101-1100	mean	0.295	0.516	0.452	0.055	0.037	0.020	0.010	0.017
	sd	0.456	0.500	0.498	0.228	0.190	0.141	0.102	0.130
	frequency	11979	132557	183028	11979	132557	183028	109928	183027
1101-3000	mean	0.193	0.359	0.271	0.054	0.059	0.033	0.014	0.022
	sd	0.395	0.480	0.445	0.227	0.236	0.178	0.119	0.145
	frequency	2539	21743	24316	2539	21743	24316	17936	24314
>3000	mean	0.177	0.335	0.218	0.056	0.061	0.037	0.015	0.031
	sd	0.382	0.472	0.413	0.230	0.239	0.189	0.120	0.173
	frequency	1194	8366	7181	1194	8366	7181	6686	7181
Total	mean	0.325	0.567	0.531	0.048	0.031	0.015	0.010	0.015
	sd	0.469	0.495	0.499	0.214	0.174	0.122	0.101	0.123
	frequency	28050	359041	592916	28050	359041	592916	306597	592908

Note: The warning system was introduced in February, 2002.

Table 4:Seller Cohorts by Buyer ProtectionRegime

	Cohort0	Cohort1	Cohort2
Total count	17595	25639	15181
% of completed listings by price range			
0-100	54.74%	61.35%	65.93%
101-1100	38.07%	31.73%	29.07%
1101-3000	5.27%	5.24%	3.62%
>3000	1.92%	1.68%	1.38%
Transaction outcomes			
% seller negative feedback	2.59%	2.05%	1.83%
% seller positive feedback	52.76%	55.62%	51.19%
% seller warning	1.06%	1.20%	2.20%

Table 5:Seller Feedback and WarningsConditional on Completion (Linear Probability Model)

	Seller NegativeFeedbacks				Seller PositiveFeedbacks				Seller Warnings
Fully covered (0<final p<=100)	0.001	0.001	0.001	-0.002*	-0.088**	-0.087**	-0.088**	-0.046**	0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
% covered (100<final p<=1100)	0.012**	0.012**	0.012**	0.004**	-0.153**	-0.153**	-0.154**	-0.076**	0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
% covered (final p>1100)	0.025**	0.025**	0.025**	0.009**	-0.232**	-0.233**	-0.233**	-0.106**	0.007**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)
ln(seller score if>0)	-0.004**	-0.011**	-0.011**	-0.008**	0.007**	0.048**	0.048**	0.030**	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)	(0.003)	(0.003)	(0.000)
Seller score is fishy	0.008**	0.006+	0.006+	0.003	-0.051**	-0.075**	-0.075**	-0.059**	0.008**
	(0.001)	(0.004)	(0.004)	(0.004)	(0.002)	(0.007)	(0.007)	(0.007)	(0.001)
Aft warranty*ln(seller score)		0.007**	0.002	0.005**		-0.041**	-0.029**	-0.033**	
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.003)	
Aft warranty*seller score is fishy		0.001	0.006	0.004		0.031**	0.001	0.011	
		(0.004)	(0.005)	(0.004)		(0.007)	(0.009)	(0.007)	
Aft warning*ln(seller score)			0.005**				-0.013**		
			(0.001)				(0.002)		
Aft warning*seller score is fishy			-0.007*				0.038**		
			(0.003)				(0.006)		
Cohort1				0.004+				-0.011*	
				(0.002)				(0.005)	
Cohort2				-0.001				-0.002	
				(0.001)				(0.004)	
Cohort1*Aftwarning				-0.004+				0.023**	
				(0.002)				(0.005)	
Observations	980007	980007	980007	980007	980007	980007	980007	980007	899505
R-squared	0.033	0.033	0.034	0.037	0.604	0.604	0.604	0.615	0.019

Note: All regressions control for final price, final price squared, final price interacted with the linear time trend, year-month fixed effects, day of week fixed effects, product category fixed effects (up to 3-level category code), seller's Eachnetage, seller's # of completed listings, buyer's Eachnetage, buyer scores, buyer region fixed effects, seller region fixed effects, and listing attributes. Robust standard errors in parentheses, +p<10%,*p<5%,**p<1%. Seller score is fishy if seller score is missing, negative or zero.

Table 6:Placebo Tests on Completed Listings in Regime 0 Only

	Seller negative feedbacks		Seller positive feedbacks	
100% covered on 0<p<100	0.008	(Assuming no buyer protection)	-0.020	(Assuming no buyer protection)
	(0.007)		(0.015)	
% covered =(p-100)/p for 100<p<1100	0.012	0.004	0.016	0.037***
	(0.011)	(0.007)	(0.020)	(0.014)
% covered=1000/p for p>1100	-0.003	-0.012	0.001	0.023
	(0.016)	(0.013)	(0.028)	(0.023)
Observations	28050	28050	28050	28050
R-squared	0.0739	0.0738	0.4535	0.4534

Note: All regressions control for final price, final price squared, final price interacted with the linear time trend, year-month fixed effects, day of week fixed effects, product category fixed effects (up to 3-level category code), seller's Eachnetage,seller's # of completed listings, buyer's Eachnetage, buyer scores, buyer region fixed effects, seller region fixed effects, and listing attributes,. + p<10%, * p<5%, ** p<1%.

Table 7:Transaction Price Conditional on Completion

	log(transaction price)			
	(1)	(2)	(3)	(4)
Buyer protection regime 1 * low-price category	0.025**	0.026**	0.025**	0.026**
	(0.009)	(0.009)	(0.009)	(0.009)
Buyer protection regime 1* high-price category	0.073*	0.071*	0.075**	0.073*
	(0.029)	(0.029)	(0.029)	(0.029)
ln(seller score if>0)	0.007**	-0.062**	-0.053**	-0.064**
	(0.001)	(0.009)	(0.004)	(0.009)
Seller score is fishy	0.245**	-0.011	0.049**	-0.011
	(0.006)	(0.021)	(0.014)	(0.021)
Afterbuyer protection * ln(seller score)		0.071**		0.017+
		(0.009)		(0.010)
Afterbuyer protection * seller score is fishy		0.274**		0.106**
		(0.022)		(0.028)
After warning * ln(seller score)			0.065**	0.059**
			(0.004)	(0.005)
After warning * seller score is fishy			0.226**	0.180**
			(0.015)	(0.019)
Constant	-33.957**	-33.499**	-33.423**	-33.330**
	(1.553)	(1.559)	(1.553)	(1.553)
Observations	980007	980007	980007	980007
R-squared	0.466	0.466	0.466	0.466

Note: All regressions include year-month fixed effects, day of week fixed effects, product category fixed effects (up to 3 level category code), level-1-category-specific linear trend, seller's Eachnet age, seller's # of completed listings, buyer's Eachnet age, seller region fixed effects, and listing attributes. Standard error in parentheses.+ p<10%; * p<5%; **p<1%. Buyer protection regime 2* low price category and Buyer protection regime 2*high price category are dropped due to collinearity. Seller score is fishy if seller score is missing, negative or zero.

Table 8: Transaction Completion

	Dummy of completion (linear probability model)			
	(1)	(2)	(3)	(4)
Buyer protection regime 1 * low-price category	-0.010**	-0.010**	-0.010**	-0.010**
	(0.002)	(0.002)	(0.002)	(0.002)
Buyer protection regime 1 * high-price category	0.013*	0.016**	0.014*	0.013*
	(0.006)	(0.006)	(0.006)	(0.006)
ln(seller score if >0)	0.033**	0.061**	0.048**	0.061**
	0.000	(0.002)	(0.001)	(0.002)
Seller score is fishy	-0.397**	-0.290**	-0.297**	-0.289**
	(0.001)	(0.004)	(0.003)	(0.004)
After buyer protection * ln(seller score)		-0.029**		-0.015**
		(0.002)		(0.002)
After buyer protection * seller score is fishy		-0.115**		-0.005
		(0.004)		(0.006)
After warning * ln(seller score)			-0.018**	-0.016**
			(0.001)	(0.001)
After warning * seller score is fishy			-0.119**	-0.121**
			(0.003)	(0.004)
Observations	1581002	1581002	1581002	1581002
R-squared	0.369	0.37	0.37	0.37

Note: All regressions include year-month fixed effects, day of week fixed effects, product category fixed effects (up to 3 level category code), level-1-category-specific linear trend, seller's Eachnet age, seller's # of completed listings, buyer's Eachnet age, seller region fixed effects, and listing attributes. Standard error in parentheses.+ p<10%; * p<5%; **p<1%.Warranty regime 2* low price category and Warranty regime 2*high price category are dropped due to collinearity. Seller score is fishy if seller score is missing, negative or zero. After warranty is a dummy which indicates the listing time is after the introduction of buyer Warranty.

Appendix Table: High and Low-Price Categories

3-level category code	High price category names (# of successful transactions)	Low price category name (top 10 by # of successful transactions)
460600	Business real estate for sale (1)	Cosmetics other brands (9493)
310112	Mobile PC (5)	Child clothes (7156)
341205	color screen Panasonic brand new gsm mobile phone (110)	Underwear pants (6152)
330111	Minolta camera (121)	Avon skin care (5802)
310111	Domestic brand computer & accessories (125)	Other jewelry/watch/glasses (5314)
341202	Motorola color screen, brand new gsm mobile phone (189)	Foreign coins (5075)
341204	Sony-Ericsson color screen, brand new gsm mobile phone (247)	Socks (4804)
341203	Samsung color screen, brand new gsm mobile phone (386)	Paid card for online access(4548)
341206	Other color screen brand new gsm mobile phone (418)	Music, Album of Original Video(4344)
340103	Three star gsm mobile phone (9405)	Kose skin care (4309)

Note: Data includes 665 product categories as defined by 3-level category code. A category is labeled high price if the 25^{th} percentile of its final price distribution (conditional on completion) is above 1100RMB; a category is labeled low price if the 90^{th} percentile of its final price distribution (conditional on completion) is below 100RMB. Conditional on having at least 100 completed listings in our sample, there are 8high-price categories and 97 low-price categories.